Informed Trading in Options or Price Pressure in Stocks? Connecting the DOTS in Option-Based Return Predictability

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Abstract

The distance between option-implied and traded stock prices (DOTS) predicts future stock returns. A trading strategy based on DOTS yields an alpha of 82 basis points on the day after portfolio formation. We show that DOTS is strongly related to return reversals, order imbalances, and transaction costs in stocks, but not much related to measures of trading activity in options. These results suggest that pressure in stock prices is an important driver of the option-based return predictability. This significantly affects the interpretation of measures of informed trading based on option-implied volatilities, which are very sensitive to pressure in stock prices.

JEL Classification: G11, G12, C13

Keywords: Price Pressure, Put-Call Parity, Return Predictability, Informed Trading

1 Introduction

The difference between traded stock prices and put-call parity implied values has been attributed to the informational efficiency of options markets relative to stock markets. We offer an alternate explanation: price pressure in the stock market. In the absence of transaction costs, the put-call parity relation links the values of European puts and calls with common maturity and strike price to the value of the underlying stock, and a violation of the parity relation presents an arbitrage opportunity. However, given American options and transaction costs, the put-call parity relation provide bounds on the bid and ask prices of a stock given the bid and ask prices of options on that stock. In this setting, the link between stock and option markets need not be tight and the no-arbitrage stock price range implied by option prices can be wide. The stock price can therefore vary within the option-implied bounds without necessarily leading to updates in option prices. We show that much of this variation can be explained by stock price pressure.

The midpoint of the upper and lower price bounds implied by options provides a noisy proxy for the fundamental value of the stock. In the event of upward price pressure on the stock, the traded stock price can be pushed above its fundamental value as proxied by the option-implied midpoint price and is then expected to fall in the short-term. Conversely, in the event of downward price pressure, the traded stock price can be pushed below the option-implied midpoint price and will then be expected to rise. We show that this is indeed the case, and that the distance between the option-implied midpoint price and the traded stock price (labelled as $DOTS$) is a strong predictor of future stock returns. When portfolios are formed based on our $DOTS$ measure on the last trading day of each month, the spread in one-day risk-adjusted returns between the decile of stocks experiencing the greatest selling pressure versus the decile experiencing the greatest buying pressure is economically large at 82 bps on the first day after portfolio formation. This return predictability decays significantly (or vanishes altogether) in subsequent days.

An, Ang, Bali, and Cakici (2014) and Cremers and Weinbaum (2010) provide an alternate explanation for differences between option-implied values and stock prices, namely that information that moves a stock's fundamental value impacts option prices before being fully incorporated into stock prices. Both the price pressure and the informational advantage of the options market explanations predict that when the option-implied price exceeds (is less than) the stock price, the subsequent price move is expected to be positive (negative). In order to empirically distinguish these two explanations, we examine past stock price changes and characteristics of the past trade in the stock and options markets. If stock prices are above (below) option-implied values as a result of temporary buying (selling) pressure, then we expect positive (negative) stock returns and a greater (smaller) than normal fraction of buyer-initiated trades in the prior period. If the explanation is that news is reflected in option prices before it is fully reflected in stock prices, then we expect to see greater trading in the options market (rather than unusual stock returns or abnormal order imbalance) in the prior period.

We find a strong relation between the future return on the set of stocks with extreme *DOTS* and their past stock returns as well as abnormal order imbalances and bid-ask spreads in the stock market, supporting the temporary price pressure argument. Additionally, our findings on cross-predictability of stock returns are unaffected when we restrict our analysis to the subset of stocks with zero trading in options in the prior period, inconsistent with greater informational efficiency of the options market being the source. Moreover, the cross-market predictability of *DOTS* is strongest when there is a withdrawal of liquidity supply in the stock market as argued in Nagel (2012), such as during periods of high values of VIX. Our findings are also robust to controlling for other predictive firm characteristics and risk factors drawn from both the equity and option markets. [1] Therefore, the short-term stock return predictability based on the *DOTS* measure can be thought of as a measure of

[1] We control for the ratio of option to stock trading volume (*O/S Ratio*) measure of informed trading considered in Roll, Schwartz, and Subrahmanyam (2010) and Johnson and So (2012). The *O/S Ratio* is inversely related to abnormal stock returns around the earnings announcements, which suggests that option trading improves market efficiency. In the Internet Appendix, we establish that our findings are also robust to the variables considered in Xing, Zhang, and Zhao (2010) and to the variables considered in Bali and Hovakimian (2009).

the potential return to liquidity provision for stocks that have suffered temporary supply or demand shocks.

We do not rule out the possibility that the predictive ability of *DOTS* could be partly associated with informed trading in the options market. We propose a simple approach to decompose the predictability of *DOTS* into a part that is more likely to be attributable to price pressure in the stock market and a part more likely to be related to informed trading in the options market. We argue that a low value of *DOTS* (i.e., the traded stock price is below the option-implied price) is more likely to reflect temporary selling pressure in the stock market when there is also more seller-initiated than buyer-initiated stock trades. Similarly, a high value of *DOTS* reflects buying pressure when it coincides with more buyer-initiated than seller-initiated stock trades. However, when the stock order imbalance signal disagrees with the *DOTS* signal (i.e. a low (high) value of *DOTS* coincides with a high (low) ratio of buyer-initiated to seller-initiated stock trades), then it is more likely that those are instances in which there is informed trading in the options market. We make use of this rationale to decompose the predictability of *DOTS*, and show that the magnitude of the returns of the *DOTS* strategy is almost three times larger when there is a high likelihood of price pressure in stocks (71 bps), compared to instances when there is a high likelihood of informed trading in options (25 bps).

Our evidence implies that in the presence of price pressure, traded stock prices are not good estimates of fundamental stock value. If the traded stock price is temporarily under pressure while option quotes more accurately reflects the stock's fundamental value, option metrics such as option implied volatility based on the traded stock price will reflect such stock mispricing. For example, Cremers and Weinbaum (2010) examine informed trading in the options market based on the link between the spread in implied volatilities between pairs of calls and puts and future stock returns. [2] Their implied volatility spread measure is related to our *DOTS* measure as both attempt to capture the difference between the traded

[2]Starting with Black (1975), a body of research argues that option markets rather stock markets are the preferred trading venue for informed investors. This is formalized in the theoretical model of Easley, O'Hara, and Srinivas (1998).

stock price and the option put-call parity implied prices. Similarly, An et al. (2014) examine the link between changes in implied volatilities and future stock returns. They document that stocks that experience a large increase in call (put) option implied volatilities tend to have high (low) future returns. However, their measure of innovations in implied volatility is also related to *DOTS*, as a decrease (increase) in the traded stock price relative to the option-implied value will lead to an increase in the call option implied volatility. Hence, our evidence suggests that price pressure is an important component of the predictability in stock returns documented in Cremers and Weinbaum (2010) and An et al. (2014). More importantly, using option-implied midpoint stock values instead of traded stock prices to calculate option sensitivities is likely to yield cleaner metrics and improved hedging ratios.[3,4]

Our findings complement those in Muravyev, Pearson, and Broussard (2013), who use high frequency data to show that option quotes rather than stock quotes adjust whenever a violation of put-call parity occurs. While Muravyev et al. (2013) suggests that price discovery takes place in the stock market rather than in options, we show that the position of the traded stock price within the no-arbitrage range implied by put-call parity captures price dislocations arising from demand and supply shocks in the stock market.

Our paper is also related to Ofek, Richardson, and Whitelaw (2004), which examines the relation between traded stock prices and prices implied by the put-call parity relation. Ofek et al. (2004) document that violations of put-call parity are asymmetric in the direction of short sales constraints, i.e. future returns are low when the observed price is above the implied price, with this relation being stronger for stocks with high short sale costs. Ofek et al. (2004) interpret their result as consistent with a behavioral finance theory of over-optimistic

[3]Our findings may also be relevant when studying other option metrics. For example, Bali and Hovakimian (2009) show that the difference between realized and implied volatilities predicts future stock returns and interpret this result as the outcome of investors demanding a return for bearing volatility risk. Xing et al. (2010) use the implied volatility smirk to predict future stock returns and conclude that informed traders with negative news trade out-of-the-money put options and that the equity market is slow to incorporate the information embedded in the volatility smirk.

[4]Manaster and Rendleman (1982) are the first to back out implied stock prices from option prices. They invert the Black and Scholes (1973) option pricing formula to determine the stock value and volatility pair that best fits the observed prices of a set of options written on the stock. The result depends naturally on the validity of the Black-Scholes formula. In contrast, our option-implied stock value is not dependent on the validity of a specific option pricing model.

stock investors along with segmentation of the stock and options markets. In contrast to Ofek et al. (2004), we show that there is predictability in stock returns in both the long and short legs of our strategy and that this predictability is consistent with temporary price pressure rather than an unspecified behavioral model of optimism. Additionally, segmentation between the option and stock markets reflects the greater elasticity of supply for options than stock and the transactions costs involved in synthesizing stock positions using options.

The remainder of this paper is structured as follows. In Section 2, we describe our $DOTS$ measure of temporary price pressure and the link with papers that use implied volatility metrics to predict stock returns. In Section 3, we set out the data sources and provide descriptive statistics of our sample. In Section 4, we use portfolio and firm-level cross-sectional regressions to document the extent to which our temporary price pressure measure predicts the cross-section of stock returns. We also provide direct evidence that the predictive power of our measure is driven by price pressure in the stock market rather than by informed trading in the options market. We further study how the profitability of a trading strategy based on our measure depends on the state of the market. In particular, we examine how the strategy's profitability changes during periods of financial market turmoil, i.e., during periods when there is a withdrawal of liquidity supply and return reversals become more pronounced. Section 5 contains our conclusions.

2 Option-Implied and Traded Stock Prices

In this section, we set out the bounds on bid and ask stock prices implied by the put-call parity relation in the presence of option transaction costs. The no-arbitrage bounds are then used to develop an option-implied estimate of a stock's value which, when contrasted with the traded stock price, provides a signal of the existence of temporary price pressures in the stock market and/or informed trading in the options market. We also show that the distance between the option-implied and traded stock price, abbreviated as $DOTS$, is closely related to the implied volatility difference measures examined in Cremers and Weinbaum (2010) and

An et al. (2014).

2.1 No-Arbitrage Bounds implied by Put-Call Parity

In a frictionless world put-call parity ties the values of European puts and calls with a common maturity T and strike price K to the value of the underlying asset and any violation presents an arbitrage opportunity. In the presence of transaction costs and American style options, put-call parity provides bounds on a stock's bid and ask price in terms of the options' bid and ask prices.

The put-call parity implied lower bound on a stock's ask price, S_{ask}, is

$$S_{ask} \geq S^L \equiv C_{bid} + Ke^{-rT} - P_{ask}, \tag{1}$$

where S^L is the no-arbitrage lower bound on the stock's ask price, C_{bid} is the bid price of an American-style call option, P_{ask} is the ask price of an American put, and r denotes the continuously compounded risk-free rate.[5] With analogous notation, the upper bound on a stock's bid price is

$$S_{bid} \leq S^U \equiv C_{ask} + K + PV(\text{Div}) - P_{bid}, \tag{2}$$

where $PV(\text{Div})$ denotes the present value of the dividends to be paid on the stock over the option's life. An ask price for the stock that satisfies the lower bound in (1) precludes arbitrage from going long in the stock and short in a synthetic stock (by selling a call, buying a put and borrowing the present value of the strike price). A bid price for the stock that satisfies the upper bound in (2) precludes arbitrage from shorting the stock and buying a

[5]Unlike the bounds given European options, the lower bound in relation (1) on a stock's ask price implied by put-call parity and American options does not involve the present value of the dividends to be paid over the remaining life of the options. Relation (1) sets out the condition that must be satisfied in order to preclude arbitrage from a strategy of buying a share, selling a call, borrowing the present value of the exercise price, and buying a put. If the bound were violated this strategy would yield an immediate profit. If the American call were exercised against you prior to maturity and the dividends lost to the new owner of the share, the exercise price received would be at least enough to repay the borrowing plus accumulated interest and you will retain both the put and the original profit.

synthetic payoff which dominates that from the stock (by buying a call, selling a put, lending the strike price and buying the right to any dividend paid on the stock over the options' life). The lower and upper bounds given by (1) and (2) are conservative. An arbitrageur who borrows at a rate above the risk-free rate will require S_{ask} to be strictly below S^L in order to break even. And an arbitrageur who lends at a rate below the risk-free rate will require S_{bid} to be strictly above S^U in order to break even.[6]

From (1) and (2) it is clear that the bid-ask spread on options is an important determinant of the no-arbitrage bounds on a stock's bid and ask prices. The bid-ask spread component of the transaction cost of trading in options is large, both in dollar terms and relative terms. In the sample detailed in Section 3, the average spread for a short-maturity, liquid option is 25 cents, or about 33% of a simple average of the option's bid and ask prices. The minimum possible difference between S^L and S^U is the sum of the bid-ask spreads for the call and put options in the pair, that is $(C_{ask} - C_{bid}) + (P_{ask} - P_{bid})$. This would be the difference if there is no possibility of dividends over the options' life and the risk-free rate is zero. With an average option bid-ask spread in our sample of \$0.25 and an average stock price of \$35, the resulting minimum no-arbitrage price range is equal to an economically meaningful 1.4%, illustrating that while stock and option markets are linked, the linkage need not be tight.

2.2 The Distance between Option-Implied and Traded Stock Prices (*DOTS*)

The relatively wide no-arbitrage bounds on the stocks bid and ask prices implied by option prices allow for incomplete transmission of shocks between the two different markets. Thus, a demand/supply shock in the stock market will not necessarily be propagated to the options market. This result is consistent with the fact that stocks are in fixed supply while options contracts can be easily created by traders, implying a relatively high elasticity of supply

[6] A counterbalancing force is that actual option trades might take place within the posted quotes which would reduce the width of the stock price bounds. While we do not have access to option transaction data necessary to directly investigate this possibility, Muravyev and Pearson (2015) report that 84% of option trades occur at the best bid or ask in their sample of options on 39 liquid stocks between 2003 and 2006.

in options compared to stocks. On the other hand, if there is informed trading in option markets which causes changes in option prices, these changes will not automatically cause the stock price to change by a commensurate amount. In both cases, the difference between the traded stock price and a measure of the stocks value inferred from option prices will predict future stock returns.

We propose the midpoint of the upper and lower price bounds implied by a call and put option pair j as a noisy estimate of the underlying stock i's fundamental value at time t. The distance between the option-implied measure of fundamental stock value and the traded stock price provides a noisy estimate of the combined effect of temporary price pressure in stock i's traded price at time t and the price effect of informed trading in option pair j of stock i at time t,

$$\mathrm{DOTS}_{ijt} = \frac{S_{it} - \frac{S^U_{ijt}+S^L_{ijt}}{2}}{S_{it}}, \tag{3}$$

where S_{it} is stock i's closing price on date t.

Equations (1) and (2) show that the dollar spread on options determines the width of the option-implied bounds, with tighter bounds provided by options with smaller spreads. Thus, in order to reduce the noise in our estimate of stock i's *DOTS* measure on date t, we take a weighted-average across option pairs of all the DOTS_{ijt} estimates with weights given by the inverse of the sum of the each option pair's spreads, i.e., by the inverse of the sum $(C^{ijt}_{ask} - C^{ijt}_{bid}) + (P^{ijt}_{ask} - P^{ijt}_{bid})$,

$$\mathrm{DOTS}_{it} = 100 \sum_{j=1}^{J} \frac{\left(C^{ijt}_{ask} - C^{ijt}_{bid} + P^{ijt}_{ask} - P^{ijt}_{bid}\right)^{-1}}{\sum_{k=1}^{J} \left(C^{ikt}_{ask} - C^{ikt}_{bid} + P^{ikt}_{ask} - P^{ikt}_{bid}\right)^{-1}} \mathrm{DOTS}_{ijt}, \tag{4}$$

where J is the number of option pairs. The resultant *DOTS* estimate is positive (negative) if the traded stock price is greater than (less than) the option-implied mid-point; i.e., the *DOTS* measure will tend to be positive (negative) if the price of a stock has experienced upward (downward) price pressure or if informed traders in the option market have traded on negative (positive) private information.

Since our $DOTS$ measure reflects the difference between traded and option-implied stock prices, it is prudent to consider the extent to which option-implied prices are affected by temporary price pressure in the options market. In the model of Gârleanu, Pedersen, and Poteshman (2009), option market demand/supply shocks have the same effect on the price of a put and a call with the same strike and maturity. From (1) and (2) we see that both S^L and S^U are unaffected by equal changes in the prices of the call and put in a pair. As in the Gârleanu et al. (2009) setting, option-implied prices and our $DOTS$ estimates are not affected by buying/selling pressure in the options market. More generally, the impact of option demand/supply shocks on option-implied stock prices are limited because of the relatively large elasticity of option supply.

2.3 Temporary Price Pressure versus Informed Trading in Options

Since temporary price pressure moves a traded stock price away from its fundamental value, we argue that a difference between an option-implied price and a stock's traded price (or $DOTS$) can represent price pressure in the stock market. An et al. (2014) and Cremers and Weinbaum (2010) provide an alternate explanation: information that moves a stock's fundamental value impacts the options implied price before being fully incorporated in the stock price. In both explanations, positive (negative) $DOTS$ predicts *subsequent* price movements to be negative (positive). In order to empirically distinguish the two explanations, we examine *past* stock price changes and characteristics of the trades in the stock and options markets in the prior period.

If positive $DOTS$ are the result of temporary buying pressure, then we expect the stock's return to be positive and a large fraction stock trades to be buyer-initiated *in the recent past*. Conversely, if negative $DOTS$ are due to temporary selling pressure, then we expect to see negative stock returns and abnormal seller-initiated trades in the prior period. If the explanation is that news is reflected in option prices before it is fully incorporated in transacted stock prices, we do not expect unusual past stock returns or an unusual stock order imbalance in the recent past.

The *DOTS* measure is closely related to the measures examined in Cremers and Weinbaum (2010) and An et al. (2014). The Cremers-Weinbaum measure is computed as the difference in the implied volatilities of puts and calls with the same strike and maturity , averaged over all option pairs on a given stock and date. Cremers and Weinbaum (2010) suggest that the implied volatility of calls is greater (less) than that of puts when call (put) prices has been bid up by informed investors with positive (negative) information and that informed traders choose to trade first in the options market. The informed trading causes the option-implied stock price to rise (fall), and subsequently spills over to the stock market leading to positive (negative) future stock returns.

Suppose temporary buy pressure leads a stock's observed price to exceed its fundamental value but option prices do not fully reflect the stock price pressure, as discussed in Section 2.2. The observed prices of calls (puts) will then appear to be low (high) relative to the stock price given buy pressure. To explain the call prices via the Black-Scholes model requires volatility inputs that are lower than the volatility inputs that explain the put prices. Further, given the fundamental value of the stock, the implied volatility difference between puts and calls (with the same strike and maturity) is increasing in the traded stock price.[7] We find that the correlation between *DOTS* and the Cremers-Weinbaum implied volatility spread measure is 95%, indicating that these two measures capture a similar phenomenon, which we argue is related to trading frictions in the underlying stock.

An et al. (2014) examine the difference between the monthly change in short-term at-the-money put option implied volatility and the change in short-term at-the-money call option implied volatility. Like Cremers and Weinbaum (2010), An et al. (2014) interpret a greater increase in call option implied volatility relative to the contemporaneous increase in put option implied volatility as a reflection of good news being incorporated into option prices

[7] Analogous results apply to option sensitivities, such as deltas, gammas, and the shape of the volatility smile.

before being fully incorporated into stock prices. Because the An et al. (2014) measure is the monthly change in the difference between at-the-money call and put implied volatilities, the An et al. (2014) measure will be affected by temporary price pressure both at the current date and one month earlier. Consistent with the An et al. (2014) measure being a noisier proxy for stock price pressure, , the correlation between *DOTS* and the An et al. (2014) measure is lower at 44%.

3 Data

In this section, we explain the data sources and describe the main characteristics of our sample.

3.1 Sample Selection

We combine several data sources in our analysis. We extract daily and monthly stock prices, returns, trading volume, and number of shares outstanding from CRSP. We retain only common stocks (share codes 10 and 11) and stocks traded on the NYSE, NASDAQ, or AMEX (exchange codes 1, 2, and 3).[8] We follow Gao and Ritter (2010) and adjust volume data for stocks trading on NASDAQ before 2004.[9]

We merge the stock data from CRSP with the daily options data from OptionMetrics, which covers the period between 1996 and 2013. We create pairs of call and put options with the same maturities and strike prices. We retain only option pairs for which both options satisfy the following restrictions: (i) they have between 5 and 36 calendar days until expiration, (ii) their bid prices are not missing and are strictly positive, (iii) their ask prices

[8]We drop stocks with a delisting return during the portfolio formation month. For stocks that delist during the month after the formation date, we determine the delisting date return from the delisting month return and the cumulative return over the prior days of the month. If there is no valid delisting return, we set the delisting month return equal to zero for delisting codes 100 to 399. Following Shumway (1997), for delisting codes 500, 520, 551-574, 580, 584 we assign a delisting month return of -30% and for other delisting codes, we assign a delisting month return of -100%. If the monthly return of a stock is not missing then any missing daily stock returns during that month are set to zero.

[9]If closing bid and ask quotes are locked (bid equal to ask) or crossed (bid larger than ask) we set them to missing.

are not missing and are strictly greater than their bid prices, (iv) their open interests are larger than zero, and (v) their deltas are not missing. In addition, we delete option pairs for which the difference between the call delta and the put delta falls outside the interval $[0.9, 1.1]$. These option filters remove penny stocks from the final sample.[10] For each stock-date, we also retain the 30-day at-the-money[11] put and call implied volatilities from the OptionMetrics volatility surface data, similar to An et al. (2014).

In order to compute the option-implied bounds from expressions (1) and (2) of Section 2, we extract continuously compounded risk-free rates from the OptionMetrics Zero Coupon Yield Curve dataset and use them to obtain the present value of the strike price and the present value of the actual dividends paid over the remaining life of the options in each put-call pair.[12] We use the OptionMetrics Dividend dataset and define a firm to be a dividend payer when there is a distribution of type 1 (i.e. cash dividends) as this is most likely to affect the option-implied stock price bounds.[13]

We obtain data on the NYSE size breakpoints, as well as time-series data on risk factors from Ken French's website. We compute risk-adjusted returns using a five factor model, which includes the market, size, and value factor, as well as the robust-minus-weak profitability and the conservative-minus-aggressive investment factors (Fama and French (2015)). Balance sheet data to compute market-to-book ratios is from Compustat.

To relate our findings to market microstructure effects induced by order imbalances and short-selling costs, we examine additional databases. High frequency data on order flow imbalances are obtained from NYSE Trade and Quote (TAQ) data for the period 1996-2010

[10] We define a penny stock as having a closing price below \$5 (\$1) before (after) April 2001.

[11] At-the-money is defined here as having an absolute delta equal to 50%.

[12] We use the standardized set of maturities for risk-free rates in OptionMetrics and linearly interpolate for other maturities. Since we discount realized dividends at the risk free rate, we do not include a compensation for dividend risk. While van Binsbergen, Brandt, and Koijen (2012) show that the risk associated with dividends to be paid over a two-year horizon is priced, the dividends we consider have almost always been announced and are payable within 36 calendar days; i.e., the dividends of relevance to our analysis are almost certain. In the Internet Appendix, we show that our results are robust to excluding dividend-paying stocks altogether.

[13] We exclude from our final sample all stocks with a liquidating dividend (LIQUID_FLAG=1), a dividend cancellation (CANCEL_FLAG=1), a stock dividend, a stock split or a special dividend (DISTR_TYPE = 2, 3, or 5, with AMOUNT > 0) between the portfolio formation date and the option expiration date as these events may give rise to adjustments in the terms of the option contracts.

(see Chordia, Roll, and Subrahmanyam (2002), Chordia and Subrahmanyam (2004))). Daily data on stock lending fees is obtained from the Markit database, which covers the period July 2006 through December 2013 (see Engelberg, Reed, and Ringgenberg (2014)).

3.2 Descriptive Statistics

Our sample includes 5,523 distinct stocks with a cross-section ranging from 599 (1996) to 1,720 (2007). On the last trading day of each month, we sort stocks into deciles based on *DOTS* calculated from closing stock prices and closing option bid-ask quotes. Table 1 reports summary statistics of characteristics of the decile portfolios over the period 1996 through 2013. Appendix A provides definitions of all variables in Table 1.

[Table 1 about here]

The average *DOTS* measure in the whole sample is nearly zero (with 49% of values positive and a median of −0.80 basis points). Panel A of Table 1 shows that the average *DOTS* in the top and bottom deciles are 0.91% and −0.78% respectively, indicating that transacted stock prices deviate substantially from option implied prices in these deciles.

As shown in Panel B of Table 1, stocks in the extreme deciles of *DOTS* have smaller market capitalization (average NYSE size decile is 4), lower prices (average price is $23), and higher idiosyncratic volatility than the other deciles. The stocks in the extreme *DOTS* deciles also exhibit larger proportional bid-ask spreads: 0.8% compared to 0.5 to 0.6% for other deciles. These characteristics of the stocks in the top and bottom *DOTS* deciles are consistent with stocks facing larger impediments to arbitrage forces. The characteristics of the options traded on the stocks in the extreme *DOTS* deciles in Panel C have similar interpretations. For instance, the spread between the option-implied lower and upper bound is wider (above 3%) for stocks in the extreme *DOTS* deciles. Wider option-implied price bounds imply a looser link between option and stock prices and a large supply shock in the stock market is less likely to lead to an arbitrage opportunity. Bid-ask spreads on the call and put options are also larger for the stocks in the extreme *DOTS* deciles, both in dollar terms and as a percent of the option mid-quote.[14]

Confirming the strong positive correlation between *DOTS* and implied volatility spreads and changes established in Section 2, the average difference between put and call implied volatility increases monotonically across the *DOTS* deciles.[15] Using the OptionMetrics volatility surface data, Table 1 shows that both weekly and monthly changes in the at-the-money put or call implied volatility, as well as the change in the difference between the at-the-money put and call implied volatility, show a monotonic pattern across the *DOTS* deciles.[16]

The univariate statistics in Table 1 provide several indictors that stocks in the low(high) *DOTS* deciles are under sell (buy) pressure in the stock market. First, the average excess returns on the formation day monotonically increases from −64bps in the bottom *DOTS* decile to 94bps in the top decile (we obtain a similar pattern in the return over the formation month). Second, the average values of Price relative to bid and ask reveal that the formation days closing stock transaction prices in low (high) *DOTS* stocks are nearer to the bid (ask) quote. Third, for the NYSE TAQ subsample (1996-2010), low *DOTS* decile stocks experience abnormally large net sell orders during the formation period, while stocks in the high *DOTS* decile have abnormally large net buy orders. Finally, average shorting fees (based on a subsample from 2006-2013) are a whopping 400bps for the high *DOTS* decile, drastically higher than the 48bps for the low *DOTS* decile. We also do not find strong indicators of more informed trading in the options data for high and low *DOTS* stocks. For instance, the average time since the calls and puts were last traded is highest for the extreme *DOTS*

[14]Since 2001 the minimum tick size on the CBOE for options with prices below $3 has been $0.05. For higher-priced options the minimum tick size has been $0.10. See `https://www.cboe.com/Products/EquityOptionSpecs.aspx`. As Table 1 of this paper shows, average option spreads are much larger than the minimum tick size.

[15]Using the standardized put and call options with a maturity of 30 calendar days and an absolute delta of 50% from the OptionMetrics volatility surface data yields a correlation of 77% between *DOTS* and the put minus call implied volatility spread.

[16]The correlation between *DOTS* and the change in the implied volatility spread over the preceding month equals 63% when the spread is measured as the open interest-weighted average implied volatility difference across the option pairs.

portfolios, indicating a lack of trading in options on these stocks.[17]

4 Predictability based on DOTS: Price Pressure in Stocks or Informed Trading in Options?

4.1 Univariate Analysis: Stock Returns on Portfolios Sorted by *DOTS*

For the decile portfolios formed by sorting on *DOTS* on the last trading day of each month (see Table 1), we evaluate the stock performance over subsequent days, rebalancing the portfolio every month. Both the informed option trading and temporary stock price pressure hypotheses predict that the stocks in the highest (lowest) *DOTS* decile will underperform (outperform) during the holding period. To capture the stock return reversals predicted by the temporary stock price pressure hypothesis but not the informed option trading hypothesis, we create a long-short portfolio that purchases the bottom *DOTS* decile of stocks and sells the top decile of stocks.

Figure 1(a) shows how the *DOTS* measure changes around the portfolio sorting date. Although high *DOTS* stocks have observed prices that are on average above option-implied mid-point prices both before and after the sorting date, deviations from pre-sorting date levels of *DOTS* build-up and subside relatively quickly around the sorting date. Figure 1(b) shows the cumulative raw and risk-adjusted returns of the long-short portfolio formed based on *DOTS*, as well as the cumulative risk-adjusted returns of the long and short legs of the portfolio around the sorting date. The patterns in this graph are consistent with strong short-term stock price reversals around the *DOTS* sorting dates. Specifically, stocks belonging to the short and long legs of the *DOTS* strategy experience price shocks on the sorting date which completely revert in the subsequent days. The strong return reversal is consistent with price pressure emanating in the stock market being an important driver of the cross-

[17] Recall that we only consider put-call pairs with non-zero open interest for both options in the pair.

predictability from the options market to the stock market.

[Figure 1 about here]

Table 2 reports daily averages of the raw and risk-adjusted returns in Figure 1(b)for different holding periods. Portfolios are formed on the last trading day of each month and held for one day after portfolio formation, for days 2 to 5 after formation, or for days 6 to 10 after formation. The return on the first day after portfolio formation is large relative to the subsequent returns. For instance, the one-day equal-weighted five-factor alpha of the long-short portfolio is 82 bps, comprised of 45 bps for the long leg and -37 bps for the short leg. The daily average equal-weighted five-factor alpha for days 2-5 and days 6-10 decays rapidly to 7 bps and 5 bps respectively.

The overnight return from the close of the sorting day to the open of the next trading day accounts for 47 bps out of the one-day return of 82 bps in Panel A of Table 2. This suggests that the return from an implementable *DOTS* strategy is lower than 82 bps. Panel B of Table 2 shows value-weighted results, which are broadly consistent with the equal-weighted results.

[Table 2 about here]

Next, we examine whether returns calculated from changes in option-implied stock values exhibit similar patterns to those calculated from traded stock prices. Figure 2(c) shows that the return reversal is absent from the option-implied stock returns, providing further evidence that the cross-predictability is driven mainly by traded stock price movements, rather than by movements in option-implied stock values. The strong return reversal in traded stock prices around the sorting date is apparent in Figure 2(a), which plots the difference between the observed stock return and the option-implied stock return.

[Figure 2 about here]

The observed stock return reversal in Figure 2(b) is weaker for the most positive (High) $DOTS$ decile than for the most negative (Low) $DOTS$ decile, which is consistent with the presence of short-sales frictions. To rule out the possibility that our results are driven by a combination of the fact that $DOTS$ decile portfolios are formed on the last trading day of the month and some type of turn-of-the-month effect, we perform the $DOTS$ sorting on other days surrounding the last trading day of the month. Figure 3 reports the returns generated when we sort the stocks based on $DOTS$ on other days of the month, ranging from eight trading days before to eight trading days after month-end. As Figure 3 shows, the returns to the $DOTS$ strategy remain qualitatively unchanged and are not affected by the particular day chosen to measure price pressure. The one-day return of the $DOTS$ strategy is however largest when using the last trading day of the month as the sorting date. This may be due to liquidity shocks around the turn of the month as documented in Etula, Rinne, Suominen, and Vaittinen (2015).

[Figure 3 about here]

4.2 Indicators of Stock Price Pressure: Evidence from the Stock Market

The results so far are consistent with the hypothesis that the predictive ability of option prices for future stock returns is driven in large part by price pressure in the stock market. In this section, we use direct indicators such as bid-ask spreads for stocks and stock order imbalances to demonstrate that our $DOTS$ measure is related to stock price pressure.

4.2.1 Stock Bid-Ask Spreads

Comerton-Forde, Hendershott, Jones, Moulton, and Seasholes (2010) and Hendershott and Menkveld (2014) argue that spreads are higher when market maker inventory levels are larger in magnitude, which happens when the specialist has absorbed a positive supply shock. Presumably this reflects a decrease in the bid price relative to the ask price as the specialist becomes less willing to acquire additional inventory. One would also expect the spread to be large when the specialist is short, or more generally holds less than their optimal inventory position having accommodated a decrease in supply/increase in demand for the stock, and raises the bid relative to the ask. Under the assumption that there is temporary pressure in stock prices, we expect to observe an increase in bid-ask spreads for the stocks that enter the *DOTS* extreme portfolios on the sorting date, and that increase should revert once the price pressure subsides.

Figure 4 shows that there is indeed a sharp increase in closing bid-ask spreads, both in dollar and relative terms, for the stocks in the extreme *DOTS* deciles on the sorting date. Moreover, the stock bid-ask spreads quickly revert back to their pre-sorting level after the sorting date, supporting the price pressure hypothesis.

[Figure 4 about here]

In Figure 4, we also observe that the dollar spreads of stocks in the extreme *DOTS* deciles are generally below the cross-sectional average, while the relative spreads are above the cross-sectional average. This is simply a reflection of the fact that stocks in the extreme *DOTS* deciles have lower prices than stocks in the remaining deciles (see Table 1).

4.2.2 Stock Order Imbalances

To provide further evidence that price pressure in the stock market is a driver of cross-market predictability, we examine order imbalances around *DOTS* sorting dates. The analysis is based on high frequency data on order flow imbalances obtained from the NYSE Trade and Quote (TAQ) data for the period 1996-2010. The data filters and computation techniques used to compute daily order imbalance measures are described in Chordia et al. (2002), Chordia and Subrahmanyam (2004). For instance, the direction of each stock transaction (i.e. buyer- or seller-initiated) is determined according to the Lee and Ready (1991) algorithm.

For each stock-day, we compute the ratio of the dollar value of buyer-initiated orders to the dollar value of seller-initiated orders or buy/sell ratio. To compute abnormal order imbalances, the benchmark is based on the 30 trading days prior to the event window $[-10, 10]$, where date 0 is the *DOTS* sorting date. For each stock and for each day in the event window $[-10, 10]$, we define the abnormal order imbalance as the difference between the buy/sell ratio of the stock and its average in the benchmark window $[-41, -11]$. Figure 5 plots the abnormal order imbalance.

[Figure 5 about here]

Figure 5 shows a striking increase in abnormal order imbalances on the *DOTS* sorting dates for stocks in the extreme *DOTS* deciles. Stocks in the low *DOTS* decile experience the biggest abnormal net selling while stocks in the high *DOTS* decile exhibit the largest abnormal net buying. The large order imbalances in the extreme *DOTS* deciles quickly revert to zero, consistent with temporary spikes in buying/selling associated with extreme *DOTS*. As detailed in the Internet Appendix, sorting stocks into deciles based on their abnormal order imbalances on the sorting date each month, and then computing the average *DOTS* measure for each of these deciles, the average *DOTS* is monotonically increasing across the order imbalance deciles. This fact provides further evidence that *DOTS* is closely related to stock order imbalances and hence to temporary price pressure.

4.2.3 Bivariate Portfolio Sorts: Controlling for Illiquidity and Short-Selling Fees

We expect the return predictability identified by *DOTS* to be stronger for stocks that are less liquid. Further, for the stocks experiencing buying pressure, we expect the return predictability to be longer lasting for the subset of the stocks with observed prices above option-implied values that have higher short-sale costs. We test these two hypotheses by examining the predictive power of *DOTS* controlling separately for stock illiquidity and short-selling costs.

We first sort stocks into quintiles based on their Amihud (2002) stock illiquidity measure over the sorting month. Then, within each illiquidity quintile, we form a second set of quintile portfolios ranked on *DOTS*. This allows us to examine the predictive power of *DOTS* after controlling for illiquidity. Portfolios are held for one day after formation, for days 2-5 after formation, and days 6-10 after formation. Table 3 reports the equal-weighted daily returns and five factor risk-adjusted returns on the extreme portfolios of the double sort.

[Table 3 about here]

As shown in Table 3, the long-short portfolio based on *DOTS* (i.e. row Low-High) exhibits a statistically significant return for the most illiquid stocks (i.e. column High ILLIQ), across all holding periods. The long-short portfolios Fama-French five-factor alpha is a large 84bps on day 1, and declines to 8pbs (over days 2-5) and 5bps (over days 6-10). However, for the most liquid stocks (i.e. column Low ILLIQ), the predictive power of *DOTS* is lower at 41bps and vanishes for holding periods that exclude the first day after portfolio formation. These findings are consistent with stock price pressure being stronger and taking longer to dissipate for more illiquid stocks. The profitability of the *DOTS* strategy for illiquid stocks is significantly greater than for liquid stocks on the first day after formation, but not on subsequent days.

We also investigate the relation between *DOTS* and short-selling costs. The short-selling cost data comes from Markit, which collects self-reported security loan rates from over 100 market participants in the security lending market. The data is available for a shorter sample period from July 2006 to December 2013. We use the weighted average of the shorting fees for newly established short positions in each stock on the sorting date (or the last available fee if that observation is missing), where the weight assigned to each loan fee is proportional to the dollar value of the loan. We first sort stocks into quintiles by short-selling fees on the sorting date and then, within each shorting fee quintile, we form a second set of quintile portfolios ranked on *DOTS*.

[Table 4 about here]

Table 4 shows that, on the first day after portfolio formation, the predictive power of *DOTS* is significant for both high and low shorting fee stocks at around 30bps. This suggests that *DOTS* provides an indication of price pressure that is independent of the prediction of low returns for stocks with high shorting fees For high shorting fee stocks the five factor alpha is only significant for the short side; i.e., for the set of stocks with high *DOTS*. The combination of a high value of the *DOTS* measure and a high shorting fee appears to be an even stronger signal that the stock is overpriced and is expected to underperform in the following days. The return on high shorting fee, high *DOTS* stocks is significantly more negative than the return on low shorting fee, high *DOTS* stocks.

For holding periods other than the first day after portfolio formation, the predictive power of *DOTS* is not statistically significantly different for stock with high versus low shorting fees. Overall, the results in Tables 3 and 4 are consistent with it being the case that stocks which are either less liquid or more costly to short are also more likely to experience price pressure which is correctly identified by our *DOTS* measure, with the strongest effect on the day following the portfolio formation date.

4.3 Indicators of Stock Price Pressure: Evidence from the Options Market

In the previous subsection, we provided direct evidence from stock-market data that *DOTS* is a proxy for price pressure in the stock market. In this subsection, we provide further evidence to this effect by examining option market trading activity and transaction cost data for options.

4.3.1 Zero Trading Volume in Options

If the stock return predictability identified by *DOTS* is driven by informed trading in options, then predictability should be absent in a subsample of stocks with zero option trading volume. Figure 1(a) shows that *DOTS* for the extreme deciles jumps on the sorting date, and reverts soon after. Therefore, we focus our analysis on those stocks in our sample with zero options traded on the month-end sorting date.[18] On average these monthly subsamples of stocks with zero options volume on the sorting date contain 281 stocks. We repeat the analysis from Section 4.1, forming decile portfolios based on *DOTS* for this subset of stocks. The returns on *DOTS* portfolios formed from stocks with zero-option volume are reported in Table 5 and are quantitatively similar to the full-sample returns in Table 2, a result which is at odds with the informed options trading hypothesis. The result is as predicted if cross-market predictability is driven by temporary price pressure in the stock market.

[Table 5 about here]

4.3.2 Penny Pilot Program

In this subsection we examine the effect of option transaction costs on the predictive power of *DOTS* by focusing on stocks that are part of the Penny Pilot Program (PPP). The PPP was introduced by the US option exchanges in February 2007, and implements a tick size reduction to one (five) cents for option prices below (above) \$3.[19] Since 2007, option exchanges have gradually added stocks to this program. By the end of 2013, about 360 of the most actively traded option classes were part of the project, accounting for about 75% of all option trading volume. On average, 225 stocks were part of the PPP during the period from February 2007 to December 2013.

As the option exchange determines which stocks are added to the program, the PPP is not an exogenous shock to transaction costs. Stocks in the program are generally large, with an average market cap of \$36.7B, and liquid, with average closing bid-ask spreads equal to 3.1 cents. The average option spreads of the PPP stocks in the sample are 12.8 (10.8) cents for call (put) options, equivalent to 13.1% (14.9%) of the call (put) mid-quote. Small option spreads reduce the difference between the S^L and S^U values that determine the

[18] Rather than applying the option filters outlined in Section 3, we use the raw option volume data from OptionMetrics to determine the set of stocks with zero volume.

[19] The standard tick size on options has been five (ten) cents for options with a price below (above) \$3 since April 2001 (see Battalio, Hatch, and Jennings (2004)).

option-implied midpoint estimate of a stock's fundamental value and this difference is equal to 0.74% of the synthetic share mid-quote on average.

In Section 2, we argue that large transaction costs in options cause the mid-point of the upper and lower option-implied price bounds to be a noisy estimate of a stock's fundamental value. Following that reasoning, we expect $DOTS$ for stocks with lower option spreads to be less noisy and therefore more informative about price pressure in the stock market and/or informed trading in options. To examine this hypothesis, we construct decile portfolios sorted by $DOTS$ for the subsample of PPP stocks in Table 6. Portfolio returns and alphas on the first holding day are large, both for the equal-weighted portfolio (alpha 49 bps) and for the value-weighted portfolio (alpha 48 bps). Even with the short sample period (84 months) and small sample size (46 stocks in the long-short portfolio), the alpha of the long-short portfolio is statistically significantly different from zero at the 1% level, confirming the hypothesis that lower option transaction costs increase $DOTS$'s signal-to-noise ratio. For holding periods past the first day after sorting, the long-short portfolio returns quickly decrease towards zero and are not statistically different from zero at conventional significance levels. The evidence in this section again shows that the data is consistent with the efficacy of the DOTS measure.

[Table 6 about here]

4.4 Decomposition of Return Predictability: Price Pressure vs Informed Trading

So far, the findings suggest that $DOTS$ predicts stock returns mainly because of the price pressure in the underlying stock itself. However, as outlined in Section 2, $DOTS$ could also reflect informed trading in the options market, with option prices leading stock prices. In this section we propose a simple approach to decompose the predictability of $DOTS$ into a part that is more likely to be attributable to price pressure in the stock market and a part that is possibly related to informed trading in the options market.

As we argue in Section 4.2.2, when a low (high) *DOTS* value reflects selling (buying) pressure in the stock market, we expect to see more seller-initiated (buyer-initiated) stock trades in the formation period. If, on the other hand, a low(high) *DOTS* stems from positive(negative) information in the options market which does not spill over into the stock market, we do not expect to see any imbalance in buyer-initiated versus seller-initiated stock trades. In addition, to the extent that there is information leakage, i.e., stock prices partially reflecting the information impounded in option prices, we expect to see more buyer-initiated (seller-initiated) stock trades for positive (negative) information. Market makers delta-hedging trades could be one channel through which the information travels from the option to the stock market.

The preceding reasoning suggests that information about order imbalances together with *DOTS* can be used to separate price pressure from informed option trading. For the set of NYSE-listed stocks in the TAQ database over the period January 1996-December 2010, we compute daily order imbalance (*OIB*) as the ratio of the dollar value of buyer-initiated trades over the dollar value of seller-initiated stock trades. If a stocks *OIB* exceeds (falls below) the median contemporaneous value across all stocks, we argue that the stock is more likely to face buying (selling) pressure. Next, we classify stocks to be under price pressure if signals from *DOTS* and *OIB* both indicate price pressure in the stock market: for example, when *OIB* is above the cross-sectional median (Above Med OIB) and *DOTS* is high, *DOTS* is most likely to indicate buy pressure. Similarly, selling pressure is most likely when the stocks low *DOTS* coincides with Below Med OIB. When the information in *DOTS* contradicts the buy/sell pressure implied by *OIB*, we interpret the predictive ability of *DOTS* to be related to informed trading in the options market. In summary, on the last trading day of each month, we independently sort stocks into quintiles of *DOTS* and on whether the stock is Above Med OIB or Below Med OIB. We then interact the *DOTS* and *OIB* classifications and form portfolios based on different combinations of *DOTS* and *OIB*.

In Table 7 we present the results of this decomposition. In Panel A of Table 7, we focus on the portfolios that are more likely to be affected by price pressure. A simple liquidity supplying strategy that anticipates returns from price pressure involves a long position in stocks that are under sell pressure (Low DOTS and Below Med OIB) and a short position in stocks that are under buy pressure (High DOTS and Above Med OIB). The returns reported in the row labelled Day 0 (Sort Date) in Panel A confirm the price pressure hypothesis: the stocks experiencing selling pressure exhibit a large negative return of -178 bps on the formation date. The option market only partially reflects this stock price pressure with an average option-implied stock return of -105 bps. In other words, the traded stock price is pushed below the option-implied price on the formation date. The long-short liquidity supplying strategy is highly profitable: the one-day Fama-French five-factor alpha is 69 bps. The strategys returns over subsequent days decrease quickly but continue to remain statistically significant, as shown in Panel A of Table 7.

In Panel B of Table 7 we gather the stocks for which the *DOTS* signal is less consistent with price pressure and hence, is likely to reflect informed trading in the options market. For example, we expect low *DOTS* stocks to perform well even if the stocks have high buy pressure (or Above Med OIB) if *DOTS* reflects informative option prices. Consistent with this expectation, we find that the increase in the option-implied price on the sorting date (+60 bps) exceeds the increase in the traded stock price (+39 bps). Consequently, to examine the returns in subsequent days, we form the long-short strategy by going long on stocks with Low DOTS and Above Med OIB and shorting stocks with High DOTS and Below Med OIB. For the long-leg, the stock price is expected to increase further in the near future to fully reflect the positive information in the options market, which is confirmed by the long leg five-factor alpha of 14bps on the day after formation. As predicted, we also find that the negative information in the options market gets impounded in the stocks that we short, with a significant negative alpha of -14 bps on day 1. The long-short strategy of Panel B obtains a one-day alpha of 28 bps.

In contrast to the strong return reversal in Panel A, the results in Panel B show a pattern of stock return continuation, consistent with informed trading in the options market. Overall, the results in Table 7 show that the predictive ability of our *DOTS* measure has two sources:

the temporary price pressure in the stock market and informed trading in the option market. Overall, higher returns in Panel A than in Panel B suggest that price pressure in the stock market is a larger contributor to cross-market predictability than informed trading in the options market. This is also reflected in the observation that the majority of stocks in a given extreme $DOTS$ decile are classified as more likely to be affected by stock price pressure than by informed options trading, with Panel A containing 60-65% of all stocks in each extreme $DOTS$ decile. Finally, it is important to highlight that, in both panels of Table 7, the stock price systematically converges to the option-implied price, which sets the option-implied price as a better proxy for the fundamental value of the stock.

[Table 7 about here]

4.5 Longer-Term Performance of the *DOTS* Strategy

Recent work in An et al. (2014) finds that cross-predictability from options to stock prices is significant at longer horizons of up to several months. Cremers and Weinbaum (2010) documents that a strategy of going long in stocks with relatively expensive calls and going short in stocks with relatively expensive puts generates a value-weighted, five-factor risk-adjusted return of 50 bps in the week after portfolio formation. Bali and Hovakimian (2009) show that the spread between the implied volatilities of call and puts predicts future risk-adjusted stock returns over the subsequent month. Since all three studies examine holding periods longer than one day, we investigate if our $DOTS$ measure has predictive ability for portfolio returns over a period that begins after a number of rest days following the month-end sorting date and finishes at the end of the subsequent month. Table 8 reports the results given a rest period of either zero, one, or five trading days.

[Table 8 about here]

Panel A of Table 8 shows that the equal-weighted five-factor risk-adjusted returns are large and statistically significant at 1.5% per month. However, the returns decline substantially if we skip one or five days between formation and holding periods. The five-factor alpha on the equal-weighted long/short strategy reduces to 0.7% and 0.4% with one day and five day rest periods respectively.. The effect of rest days on monthly returns from the cross-predictability from options to stocks is more dramatic for the value weighted returns.[20] The long-short strategy based on *DOTS* yields a value-weighted risk-adjusted return of 0.8% in the subsequent month (comparable to evidence in the existing papers). However, the profitability of the strategy vanishes when we skip one day before implementing the strategy. Given the results on the first-day holding returns in Table 2 and in Figure 1(b), the substantial difference in returns with and without a rest day is not surprising, in particular for larger stocks.

4.6 Multivariate Analysis: Cross-Sectional Regressions with *DOTS*

In this section, we examine the link between stock returns and stock and option characteristics as well as the *DOTS* measure in a multivariate setting. We show that the predictive power of *DOTS* is not explained away by individual stock and/or option characteristics.

We use predictive variables similar to those used in An et al. (2014). The market beta of the stock, ((*BETA*), is computed by regressing monthly returns in excess of the risk-free rate on the Fama and French (1992) market factor in a set of rolling regressions using the past 36 monthly returns. The log of market capitalization of the stock, (*SIZE*), is measured at the end of the previous month. Following Fama and French (1992), the market-to-book ratio, (*MB*), is computed as the market value of equity over the book value of common equity plus balance-sheet deferred taxes, both measured at the end of the previous fiscal year. *MOM* is the cumulative return of the stock for the previous 11 months starting one month before the sorting month (Jegadeesh and Titman (1993)). We control for a short-term reversals through *REV*, which measures the cumulative return of a stock over the five trading days ending on the *DOTS* sorting date (see Jegadeesh (1990) and Lehmann (1990)). The illiquidity (*ILLIQ*)

[20] Blume and Stambaugh (1983) and Asparouhova, Bessembinder, and Kalcheva (2013) show that equal-weighted returns can be biased upwards when prices are noisy (even on a monthly frequency).

measure of Amihud (2002) is computed as the ratio of the absolute daily stock return to its dollar trading volume, averaged across all the days in the sorting month. *VOLAT* measures the annualized realized volatility of daily stock returns, computed as the standard deviation of daily stock returns during the formation month.

In addition to control variables based on stock characteristics, we include a number of predictor variables related to the options market. In particular, we control for the log of the ratio of call to put option volume over the five trading days up to and including the *DOTS* sorting date (*CP VOLUME*). This variable has been shown in prior work to predict returns (e.g. Easley et al. (1998), Pan and Poteshman (2006)). Our final control variable is the option-to-stock volume ratio (*O/S RATIO*) following Roll et al. (2010) and Johnson and So (2012).

In Table 9, we present the results of Fama and MacBeth (1973) cross-sectional regressions of individual stock returns on the day following the *DOTS* formation date on the stock and option characteristics described above and *DOTS* extreme decile dummies. *DOTS1* (*DOTS10*) equals one for stocks in the lowest (highest) *DOTS* decile. These regressions are run at the monthly frequency from January 1996 to December 2013. To account for potential autocorrelation and heteroskedasticity in the cross-sectional coefficients, we compute Newey and West (1987) standard errors on the time-series of the slope coefficients.

[Table 9 about here]

In Column (1) of Table 9 the magnitude and significance of the coefficients on *DOTS1* and *DOTS10* confirm the strong one-day returns associated with the *DOTS* strategy as reported in Table 2. The difference in the coefficients between *DOTS1* and *DOTS10* produces one-day return of about 81 bps.

In Columns (2), (3) and (4) we control for various combinations of the multiple stock and option characteristics. The coefficients on *DOTS1* and *DOTS10* remain statistically significant and the magnitude of the one-day return of the *DOTS* strategy is effectively unchanged at around 80bps.

The specifications in Columns (5) through (8) of Table 9 use data on a subsample of NYSE stocks for which we have data on stock order imbalances during the period between 1996 and 2010. Columns (6) and (8) use the same specification as Columns (2) and (4), except that we also include the variable *OIB*, which measures the order imbalance on the sorting date measured by the ratio of the dollar value of buyer-initiated trades over the dollar value of seller-initiated trades. Consistent with the results in Section 4.2.2, order imbalances on the sorting date are negatively related to future returns, yet the *DOTS1* and *DOTS10* coefficients are quantitatively unchanged compared to Columns (2) and (4), indicating that order imbalances alone cannot explain returns associated with the *DOTS* strategy.

4.7 Time-Variation in the Performance of the *DOTS* Strategy

DOTS is a reflection of market-makers' ability to absorb supply shocks in the stock market, which is influenced by the funding liquidity available to the market making sector (Brunnermeier and Pedersen (2009)). Boudt, Paulus, and Rosenthal (2014) conclude that a low TED spread is associated with a stabilizing relation between funding liquidity and market liquidity and hence relatively liquid capital markets while high TED spreads are associated with a destabilizing cycle where a decrease in market liquidity induces a decrease in funding liquidity and relatively illiquid capital markets. Nagel (2012) shows that the expected return from liquidity provision is time-varying and is high during periods when the market is under stress, measured by the level of the VIX index.

In this section, we study how the returns of the *DOTS* strategy depend on funding and market liquidity using TED and VIX as proxies for aggregate funding liquidity. If the return on the *DOTS* strategy is in part driven by stock price pressure, then *DOTS*'s contribution to the strategy's profitability should be higher when there is a withdrawal of liquidity supply, such as during market turmoil. It is difficult to imagine that informed trading in the options market is concentrated during periods of aggregate funding illiquidity. The correlation between the level of the VIX and the volume of all trade in individual equity options is -0.113.

Table 10 reports the results of predictive time-series regressions of the returns to the *DOTS* strategy on lagged funding liquidity proxies. Panel A reports the results for the long-short portfolio, and Panels B and C report the separate results for the long and the short legs of the *DOTS* strategy. The intercept of Column (1) in Panel A shows that the *DOTS* strategy produces a one-day risk-adjusted return of 82 bps, consistent with earlier results. The positive and significant coefficient on TED (measured over the five trading days up to the *DOTS* sorting date) in Panel A of Table 10 indicates that the TED spread is a strong predictor of the one-day return of the *DOTS* strategy: when funding liquidity is tight, price pressure is stronger and return predictability attributable to *DOTS* is greater. Interestingly, the TED spread is significantly related to the return on the long leg of the *DOTS* strategy, but not to the return on the short leg. This is to be expected since when funding costs are high a market-maker will be reluctant to acquire inventory and absorb selling pressure while their ability to sell inventory to accommodate buying pressure is less tied to funding costs since, as reported in Comerton-Forde et al. (2010), specialists in aggregate are net long 94% of the time.

[Table 10 about here]

Column (3) controls for the VIX. The positive and significant coefficient on VIX (defined as the average VIX over the five trading days ending on the sorting date) in Panel A suggests that the VIX is a strong predictor of the first-day return of the *DOTS* strategy. In addition, Panels B and C show that the VIX can predict the returns on both the long and the short legs of the *DOTS* strategy. This again suggests that the *DOTS* strategy's returns are at least in part driven by short-term stock price pressure which subsides during the holding period. Column (4) shows that the VIX level retains its predictive power when adding the TED spread as a control variable.

4.8 Robustness Checks

Section 1 in the Internet Appendix reports a number of robustness checks on the preceding analysis. Specifically, we show that our results continue to hold when a) we split the sample into two subperiods of equal length, b) we remove stocks from the sample for which the bid (ask) quote violates the upper (lower) bounds in (1) and (2), c) we exclude dividend-paying stocks, d) we exclude stocks that were part of the 2008 short-sale ban, and e) we exclude stocks whose market capitalisation falls below the first NYSE size quintile. These robustness checks highlight that our main findings are not driven by concerns about firm size, stock dividends, and specific time-periods.

5 Conclusions

In the presence of transaction costs, the range of no-arbitrage stock prices consistent with put-call parity is relatively wide, which limits the strength of the link between option and stock prices. This allows observed and option-implied stock prices to deviate from one another, driven by either supply/demand shocks in the stock market or by informed trading in option markets. We show that the distance between the option-implied stock value and traded stock prices, or *DOTS*, strongly predicts future stock returns. For example, when stocks are under upward price pressure or when there is trading on negative information in the options market, the traded stock price will be above the option-implied value and stock prices are expected to fall in future. Moreover, the stock price correction is expected to occur rapidly when either the price pressure diminishes or the option market information spills over to the stock market. A long-short trading strategy of buying stocks in the highest *DOTS* decile and shorting stocks in the lowest decile yields a one-day five-factor alpha of 82 bps, which rapidly diminishes over subsequent days.

We provide new evidence that the cross-predictability from option to stock prices is in a large part driven by temporary price pressure in the stock market. This is supported by the finding that returns based on *DOTS* are closely related to short-term return reversals, abnormal stock order imbalances, and transaction costs in the stock market. The predictability does not seem related to actual trading in the options market as would be expected if informed trading in the options market were the sole explanation of the strategy's profitability. Analyzing a subsample of NYSE-traded stocks, the $DOTS$ based trading strategy yields larger profits when order imbalance coincides with $DOTS$ signaling significant stock price pressure. The predictability of stock returns based on $DOTS$ is robust to controlling for firm characteristics and risk factors drawn from both equity and option markets. We also show that there is time-variation in the strength of the cross-sectional predictability of stock returns, which appears to be influenced by proxies for the withdrawal of liquidity supply in the stock market.

The results in this paper suggest that the traded stock price is not the best estimate of the fundamental stock value in the presence of price pressure. If the traded stock price is temporarily under pressure while option price quotes more accurately reflect the fundamental stock value, option metrics based on the traded stock price will reflect such stock mispricing and consequently should be interpreted with caution. Using option-implied stock values rather than traded stock prices to calculate the option sensitivities yields cleaner metrics and improved hedging ratios. This has particularly important implications for research on cross-market predictability that uses information on option-implied volatilities to explain future stock returns. These studies suggest that their predictability patterns are consistent with informed trading in the options market. However, their predictive variables are very highly correlated with our measure of temporary price pressure in the stock market. We argue that there may be an alternative interpretation for their findings based on price pressure in the stock market.

Our study does not specifically address cross-market predictability between options and stocks around specific corporate events. Lin, Lu, and Driessen (2014) present evidence of informed equity options trading around changes in analyst recommendations and earnings announcements. Augustin, Brenner, and Subrahmanyam (2015) document strong evidence of informed trading activity in equity options before the announcement of mergers and acquisitions. While beyond the scope of the current paper, it would be interesting to also examine the effects of stock market frictions around such corporate events.

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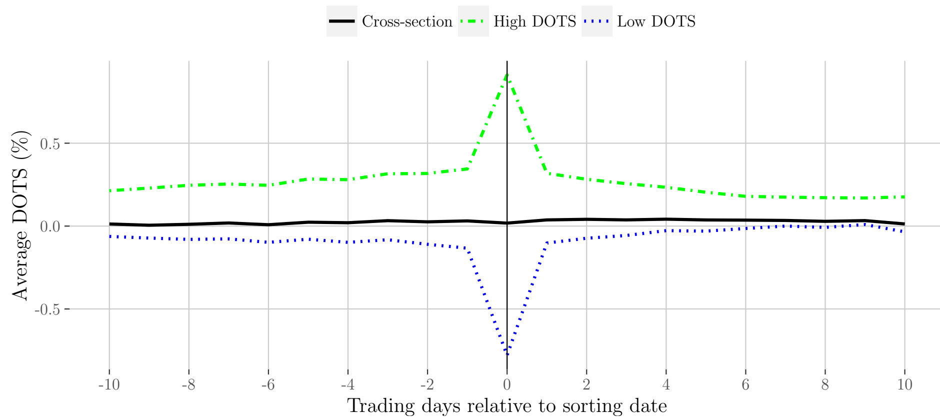
A Variable definitions

Definitions of variables used throughout the paper, constructed from the sample described in Section 3.

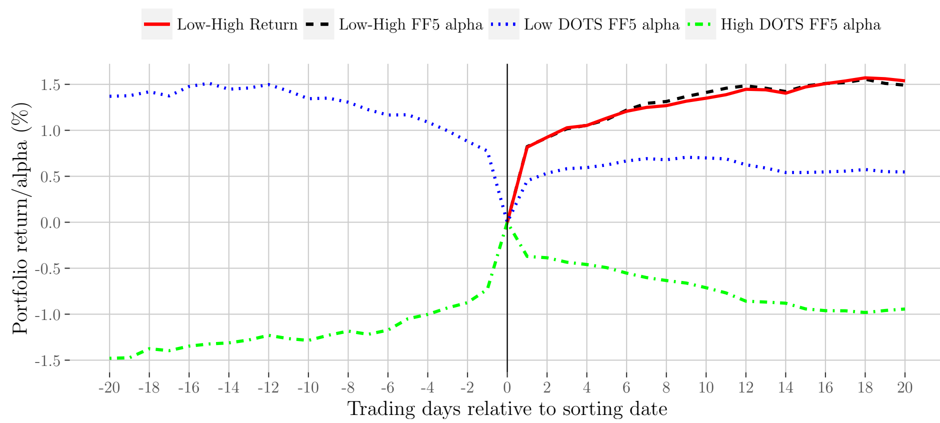
Variable Name	Definition
BETA	Regression coefficient of Fama and French (1992) market factor in 36-month rollowing window regression using monthly returns in excess of the risk-free rate.
Calls(Puts): # days since last trade	Number of calendar days since options were last traded. Computed as equal-weighted average across option contracts.
CP VOLUME	Log of the ratio of call to put option volume over the five trading days up to and including the *DOTS* sorting date.
DOTS	Distance between option-implied and traded stock prices as defined in (4).
FEE / Shorting fee	Value-weighted average shorting fee (bps) for new positions established on the *DOTS* sorting date, or the last available prior to that.
Idiosyncratic volatility	Annualized standard deviation of regression residuals of daily stock excess returns in the sorting month regressed on the five Fama and French (2015) factors.
ILLIQ	Ratio of the absolute daily stock return to its dollar trading volume, averaged across all the days in the sorting month.
Market cap	Stock price multiplied by the number of shares outstanding on the *DOTS* sorting date.
MB	Market value of equity over the book value of common equity plus balance-sheet deferred taxes, both measured at the end of the previous fiscal year.
MKTRF / SMB / HML	Daily Fama and French (1993) factors as measured on the first trading day after the *DOTS* sorting date.
MOM	Cumulative stock return for the 11 months ending the month before the sorting month.
Moneyness	Ratio of strike price over forward price corresponding to option maturity. Computed as equal-weighted average across option contracts.

Continued on next page

Variable Name	Definition
NYSE abnormal order imbalance	Order imbalance ratio in excess of the average daily order imbalance ratio over the period starting 41 trading days and ending 11 trading days before the *DOTS* sorting date.
NYSE size decile	Number between 1 and 10, with 1(10) indicating the stock's market cap on the *DOTS* sorting date falls in the smallest(largest) NYSE size decile.
OIB	Order imbalance ratio: dollar value of buyer-initiated trades over the dollar value of seller-initiated trades on the *DOTS* sorting date.
O/S RATIO	Option-to-stock volume ratio on *DOTS* sorting date following Roll et al. (2010) and Johnson and So (2012).
One week/month change in Call/(Put) IV	Change in smoothed implied volatility of a 30-day, at-the-money ($\lvert\text{delta}\rvert = 50\%$) option over the five trading days/month ending on the *DOTS* sorting date.
One week/month change in (Put IV - Call IV)	Change in put minus call implied volatility spread over the five trading days/month ending on the *DOTS* sorting date. Implied volatility is measured as the smoothed implied volatility of a 30-day, at-the-money ($\lvert\text{delta}\rvert = 50\%$) option.
Price relative to bid and ask	Stock price relative to bid-ask spread, normalised to $[0, 1]$: $\frac{\max(\min(PRC, ASK), BID) - BID}{ASK - BID}$
Put IV - Call IV	Difference between put and call implied volatility. Computed as weighted average over option pairs using sum of put and call open interest as weights.
REV	Cumulative stock return over the five trading days ending on the *DOTS* sorting date.
S^L (S^U)	Lower bound (1) (upper bound (2)). Computed as the weighted average over all option pairs, using the inverse of the option pair's bid-ask spread as weights.
SIZE	Natural log of the stock price multiplied by the number of shares outstanding, in millions of dollars, on the *DOTS* sorting date.
TED	Average TED spread in the five trading days ending on the *DOTS* sorting date.
VIX	Average VIX in the five trading days ending on the *DOTS* sorting date.
VOLAT	Annualized standard deviation of daily stock returns during the formation month.



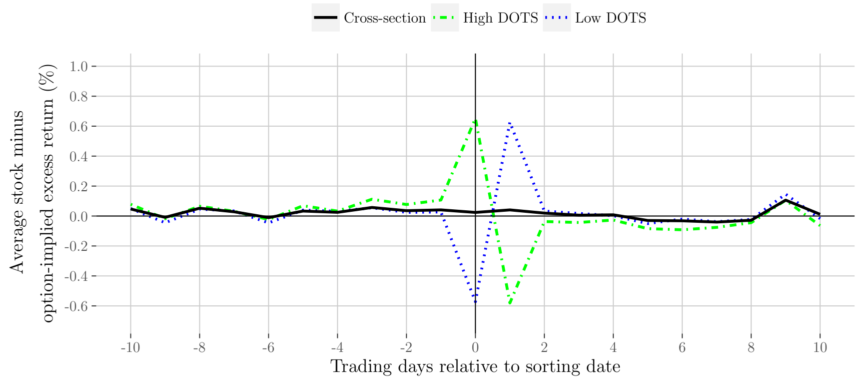
(a) Average DOTS



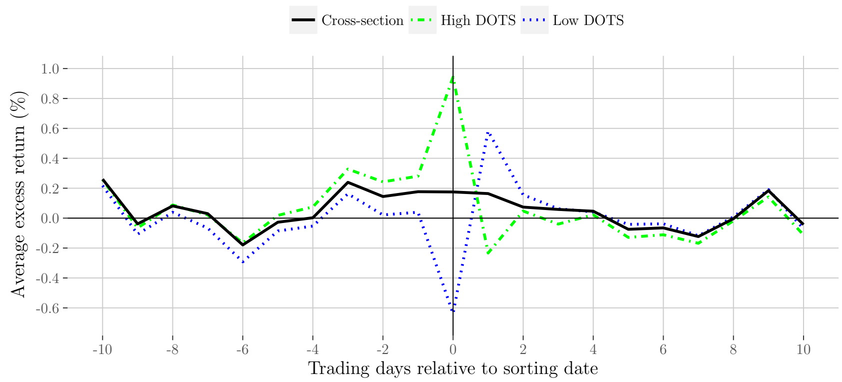
(b) Average portfolio excess return and Fama-French alphas

Figure 1: ***DOTS* and Returns around the Portfolio Formation Date**

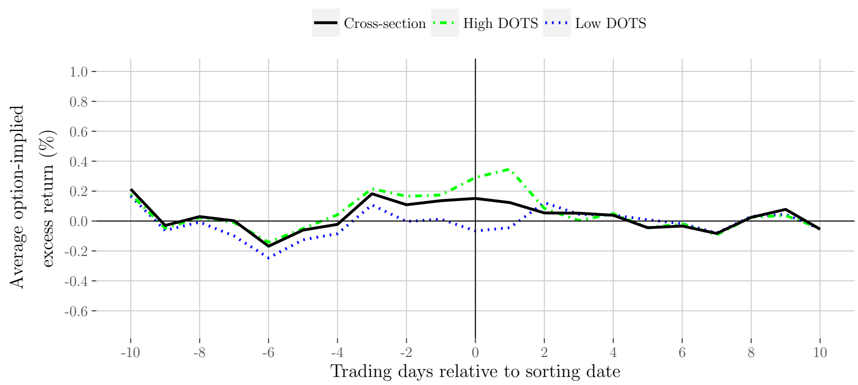
Stocks are sorted by their distance between option-implied and observed stock prices ($DOTS$) into deciles on the last trading day of the month (day zero). For the set of stocks in the extreme $DOTS$ deciles, the top panel plots the equal-weighted average $DOTS$ level from ten trading days prior to the sorting date until ten trading days after the sorting date. The average $DOTS$ across all stocks on each day is added for reference. The average is computed in the cross-section first, and then averaged across periods. For portfolios formed based on $DOTS$ on the last trading day of the month, the bottom panel plots the Fama and French (2015) five-factor alpha for different cumulative holding periods ranging from 20 trading days before the sorting date until 20 trading days after the sorting date. The dotted line corresponds to the portfolio of stocks in the lowest $DOTS$ decile, comprising the long leg of the long-short portfolio. The dash-dotted line corresponds to the portfolio of stocks in the highest $DOTS$ decile, comprising the short leg of the long-short portfolio. The dashed line corresponds to the Fama and French (2015) five-factor alpha of the long-short portfolio. The solid line corresponds to the average cumulative long-short portfolio return. The sample covers the period between January 1996 and December 2013.



(a) CRSP stock return minus option-implied stock return



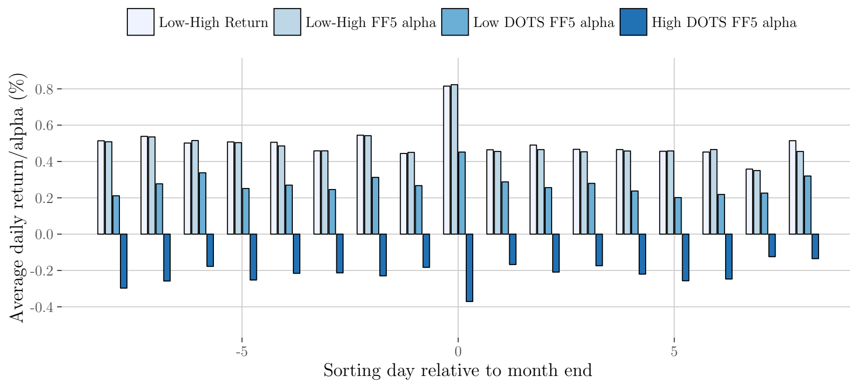
(b) CRSP stock return



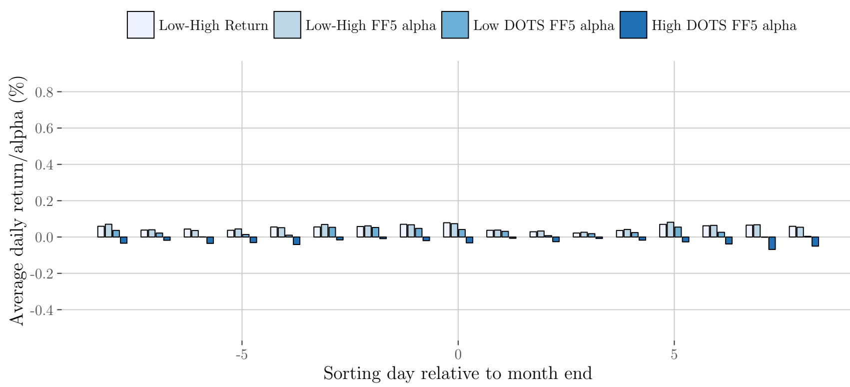
(c) Option-implied stock return

Figure 2: **Reversals of Option-Implied and Observed Stock Prices**

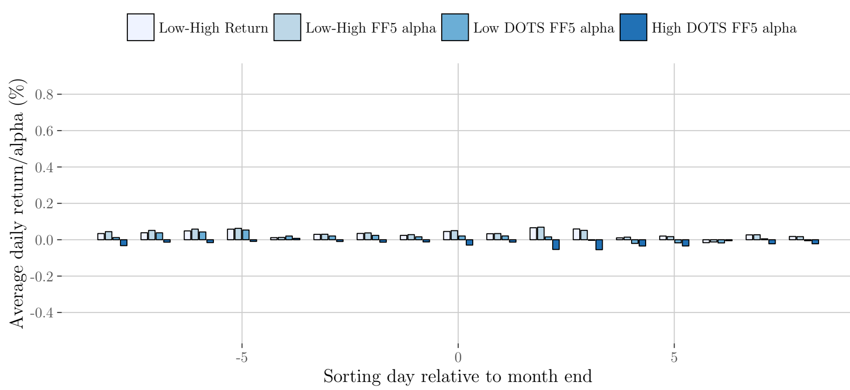
Stocks are sorted by their distance between option-implied and observed stock prices ($DOTS$) into deciles on the last trading day of the month (day zero). For the set of stocks in the extreme $DOTS$ deciles, the top panel plots the difference between the average observed stock return and the average return on the option-implied stock price (the midpoint of (1) and (2)) from ten trading days prior to the sorting date until ten trading days after the sorting date. For the same set of stocks and same period, the middle and bottom panels split this return difference into the average observed stock return (middle panel) and the average return on the option-implied stock price (bottom panel). In each graph, the dashed line corresponds to the stocks in the lowest $DOTS$ decile, comprising the long leg of the long-short portfolo. The dash-dotted line corresponds to the portfolio of stocks in the highest $DOTS$ decile, comprising the short leg of the long-short portfolio. The cross-sectional average (solid line) is added to each plot for reference. The average is computed in the cross-section first, and then averaged across periods. The sample covers the period between January 1996 and December 2013.



(a) Day 1



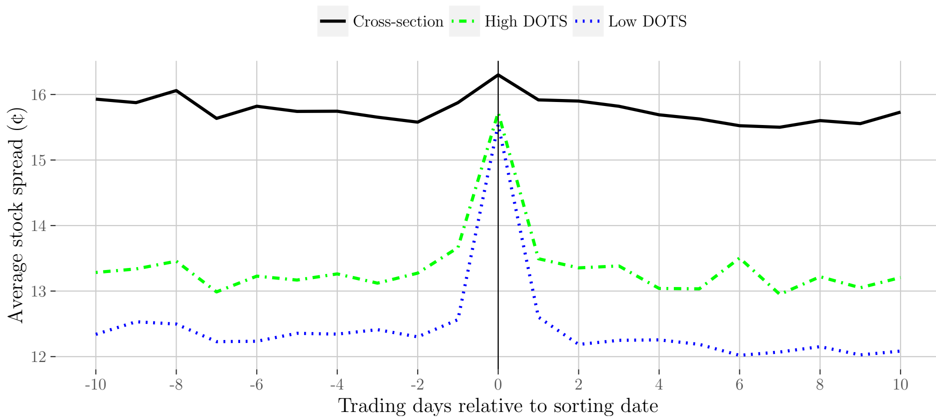
(b) Days 2-5



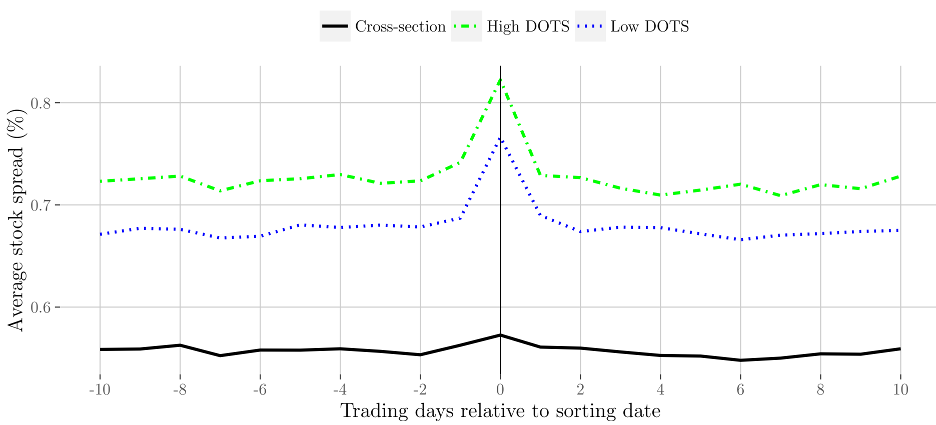
(c) Days 6-10

Figure 3: **Performance of the *DOTS* Strategy when sorting on Different Days of the Month**

Stocks are sorted by their distance between option-implied and observed stock prices (*DOTS*) into deciles on different days relative to the last trading day of the month (day zero). A long-short portfolio is formed that is long all stocks in the lowest *DOTS* decile and short all stocks in the highest *DOTS* decile. The panels plot the average daily excess return and the average daily Fama and French (2015) five-factor alpha for the long-short portfolio, and the average daily Fama and French (2015) five-factor alpha for the long and short leg separately. The top panel plots the portfolio returns and alphas for a one-day holding period from the market close on the sorting date until the market close on the next trading day. The middle panel plots the average daily returns and alphas for a four-day holding period from the market close on the first trading day after the sorting day until the market close on the fifth trading day following the sorting day. Finally, the bottom panel plots the average daily returns and alphas for a five-day holding period from the market close on the fifth trading day following the sorting day until the market close on the tenth trading day following the sorting day. The sample covers the period between January 1996 and December 2013.



(a) Average bid-ask spreads (¢)



(b) Average bid-ask spreads (%)

Figure 4: **Stock Bid-Ask Spreads around the *DOTS* Portfolio Formation Date**

Stocks are sorted by their distance between option-implied and observed stock prices (*DOTS*) into deciles on the last trading day of the month (day zero). For the set of stocks in the extreme *DOTS* deciles, the top panel plots the average closing bid-ask spread in cents from ten trading days prior to the sorting date until ten trading days after the sorting date. For the same set of stocks and same period, the middle panel plots the average closing bid-ask spread relative to the midpoint of the closing bid and ask quotes in percent. The cross-sectional average (solid line) is added to each plot for reference. The average is computed in the cross-section first, and then averaged across periods. The sample covers the period between January 1996 and December 2013.

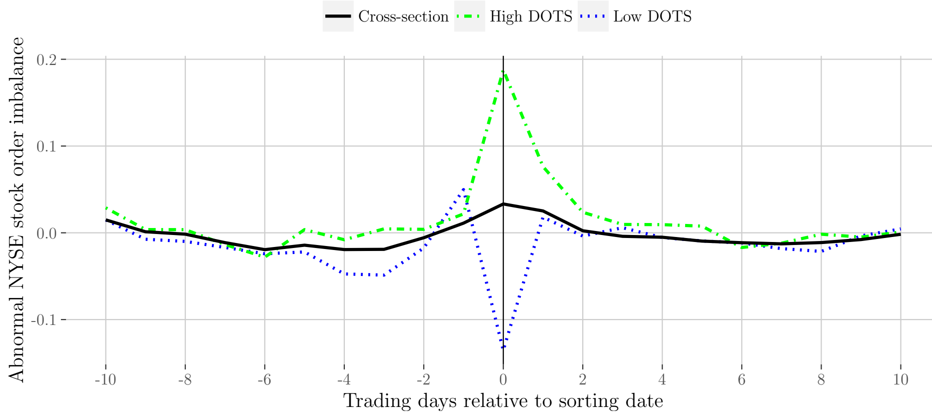


Figure 5: **NYSE Order Imbalances around *DOTS* Portfolio Formation Date**

Stocks are sorted by their distance between option-implied and observed stock prices ($DOTS$) into deciles on the last trading day of the month (day zero). For the set of stocks in the extreme $DOTS$ deciles and trading on the NYSE, the figure plots the equal-weighted average abnormal order imbalance from ten trading days prior to the sorting date until ten trading days after the sorting date. The average is computed in the cross-section first, and then averaged across periods. For a given stock-date, the order imbalance is computed as the ratio of buyer-initiated over seller-initiated trades measured in dollars in excess of the average daily ratio of buyer-initiated over seller-initiated trades in dollars during the 30 trading days ending on the 11th trading day before the sorting date. The sample covers the period between January 1999 and December 2010.

Table 1: **Characteristics of Decile Portfolios of Stocks Sorted by *DOTS***

This table reports average characteristics of decile portfolios formed by sorting optionable stocks by the distance between option-implied and observed stock prices (*DOTS*) measure. The equal-weighted averages are computed as a time-series average of cross-sectional averages. For variables based on option pairs, an equal-weighted average across the pairs is computed, with the exception of "Put IV - Call IV" (weighted by pair's open interest) and S^U/S^L (weighted by inverse of pair's bid-ask spread). The sample period equals January 1996 and December 2013, except for shorting fees (July 2006 to December 2013) and NYSE abnormal order imbalance (January 1996 to December 2010). Panel A presents the average distance between option-implied and observed stock prices measure. Panel B contains average stock characteristics. Panel C reports average option characteristics. The variables presented in this table are described in Appendix A.

Panel A: Distance between Option-Implied and Observed Stock Prices

	Low DOTS	2	3	4	5	6	7	8	9	High DOTS
DOTS (%)	−0.78	−0.31	−0.17	−0.09	−0.03	0.03	0.10	0.19	0.34	0.91

Panel B: Stock-Based Variables

	Low DOTS	2	3	4	5	6	7	8	9	High DOTS
# Stocks	129.8	129.3	129.3	129.3	129.4	129.1	129.2	129.4	129.2	129.7
Stock price ($)	22.97	31.62	37.64	42.07	43.52	42.58	39.08	36.35	31.06	23.11
Average market cap ($B)	2.91	6.07	9.48	11.99	12.72	11.76	9.62	8.09	5.70	3.18
Median market cap ($B)	0.83	1.76	2.69	3.57	3.84	3.71	3.12	2.56	1.66	0.79
NYSE size decile	4.38	5.75	6.52	6.99	7.14	7.06	6.73	6.41	5.71	4.39
Stock bid-ask spread (¢)	15.54	15.05	16.11	17.47	17.74	17.09	16.50	16.31	15.53	15.73
Stock bid-ask spread (% of midprice)	0.77	0.58	0.51	0.48	0.45	0.46	0.52	0.54	0.61	0.82
Excess return over sorting month (%)	−0.70	0.44	1.08	1.36	1.65	1.90	1.92	1.80	2.04	2.28
Excess return on sorting day (%)	−0.64	−0.21	−0.11	0.01	0.15	0.26	0.34	0.42	0.58	0.94
Price relative to bid and ask	0.27	0.31	0.37	0.45	0.54	0.61	0.67	0.72	0.75	0.77
Idiosyncratic volatility (annualised %)	44.10	37.57	34.65	32.75	32.13	33.00	34.08	35.61	38.60	46.14
Shorting fee (bps)	48.22	32.88	27.94	25.22	26.52	28.16	32.62	41.35	72.80	398.03
NYSE abnormal order imbalance	−0.14	−0.10	−0.08	−0.02	0.04	0.06	0.12	0.12	0.15	0.19

Panel C: Option-Based Variables

	Low DOTS	2	3	4	5	6	7	8	9	High DOTS
# Option pairs	1.68	2.26	2.67	2.99	3.11	3.09	2.87	2.67	2.27	1.80
$S^U - S^L$ (¢)	64.11	54.42	52.77	51.97	52.20	52.13	51.68	53.81	55.97	63.23
$\frac{S^U - S^L}{(S^U + S^L)/2}$ (%)	3.30	2.15	1.77	1.57	1.51	1.55	1.71	1.85	2.22	3.31
Moneyness	0.999	0.995	0.992	0.991	0.991	0.993	0.994	1.000	1.002	1.010
Call bid-ask spread (¢)	32.90	26.67	25.21	24.30	23.88	23.52	23.26	23.59	24.34	26.61
Put bid-ask spread (¢)	27.70	23.54	22.38	21.66	21.65	21.77	22.06	23.38	25.17	30.98
Call bid-ask spread (% of midprice)	37.14	30.06	27.20	25.71	25.65	26.29	27.96	30.02	33.24	41.68
Put bid-ask spread (% of midprice)	45.29	37.05	33.92	32.01	31.37	30.85	31.35	30.73	32.63	35.90
Put IV - Call IV (%)	−9.44	−3.65	−1.85	−0.66	0.34	1.27	2.26	3.45	5.40	12.10
One week change in Call IV (%-points)	2.42	0.57	0.05	−0.22	−0.44	−0.71	−0.93	−1.23	−1.74	−3.27
One month change in Call IV (%-points)	3.31	1.08	0.48	0.11	−0.19	−0.37	−0.70	−0.92	−1.41	−3.08
One week change in Put IV (%-points)	−2.83	−1.55	−1.13	−0.89	−0.66	−0.62	−0.46	−0.27	0.03	1.39
One month change in Put IV (%-points)	−2.15	−1.03	−0.72	−0.49	−0.34	−0.22	−0.06	0.13	0.57	2.44
One month change in (Put IV - Call IV) (%-points)	−5.46	−2.11	−1.20	−0.60	−0.15	0.15	0.64	1.05	1.98	5.52
Calls: # days since last trade	5.31	4.53	3.94	3.63	3.59	3.41	3.72	3.59	3.92	4.09
Puts: # days since last trade	8.99	7.34	6.49	5.78	5.60	5.73	6.44	6.41	7.47	8.82

Table 2: **Univariate Decile Portfolios of Stocks Sorted by *DOTS***

This table reports excess returns (Return) and Fama and French (2015) five-factor alphas (FF5 Alpha) of portfolios formed based on the distance between option-implied and observed stock prices (*DOTS*). These are daily average figures, for holding periods that include the first day after portfolio formation (Day 1), the second to fifth day after formation (Days 2-5), and the sixth to tenth day after formation (Days 6-10). Portfolio 1 (Low DOTS) contains stocks with the lowest *DOTS*, and Portfolio 10 (High DOTS) contains stocks with the highest *DOTS* on the last trading day of the month. Panel A presents the results for equal-weighted returns across the stocks in each decile, and Panel B presents value-weighted returns, using the stocks' market capitalisations on the sorting date as weights. Column Low-High represents the results for buying the "Low DOTS" portfolio and shorting the "High DOTS" portfolio. The statistical significance of the average returns and alphas is represented by asterisks, where ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively. Newey and West (1987) standard errors are reported in parenthesis.

Panel A: Equal-Weighted Portfolios

Holding Period		Low DOTS	2	3	4	5	6	7	8	9	High DOTS	Low-High
Day 1	Return	0.583***	0.349***	0.265**	0.248**	0.176	0.167	0.086	0.053	−0.053	−0.233*	0.816***
		(0.130)	(0.112)	(0.110)	(0.110)	(0.111)	(0.111)	(0.116)	(0.113)	(0.123)	(0.131)	(0.095)
	FF5 alpha	0.452***	0.208***	0.078***	0.072***	0.001	−0.008	−0.080***	−0.113***	−0.205***	−0.372***	0.823***
		(0.063)	(0.038)	(0.026)	(0.028)	(0.021)	(0.020)	(0.026)	(0.029)	(0.038)	(0.054)	(0.098)
Days 2 - 5	Return	0.058	0.034	0.040	0.055	0.044	0.047	0.000	0.017	0.016	−0.020	0.079***
		(0.059)	(0.054)	(0.053)	(0.050)	(0.051)	(0.051)	(0.049)	(0.053)	(0.056)	(0.058)	(0.022)
	FF5 alpha	0.041**	0.013	0.021*	0.029***	0.021**	0.022**	−0.017	−0.003	0.004	−0.032*	0.073***
		(0.020)	(0.011)	(0.012)	(0.011)	(0.011)	(0.010)	(0.012)	(0.013)	(0.014)	(0.017)	(0.022)
Days 6 - 10	Return	−0.006	−0.004	0.014	−0.021	0.002	−0.006	−0.007	−0.010	−0.019	−0.051	0.045**
		(0.049)	(0.044)	(0.041)	(0.045)	(0.041)	(0.041)	(0.041)	(0.046)	(0.046)	(0.051)	(0.019)
	FF5 alpha	0.020	0.015	0.032***	−0.003	0.021**	0.014	0.013	0.008	−0.001	−0.030	0.050***
		(0.019)	(0.011)	(0.011)	(0.008)	(0.010)	(0.009)	(0.013)	(0.013)	(0.014)	(0.020)	(0.018)

Panel B: Value-Weighted Portfolios

Holding Period		Low DOTS	2	3	4	5	6	7	8	9	High DOTS	Low-High
Day 1	Return	0.599***	0.470***	0.373***	0.308***	0.268**	0.192*	0.129	0.109	0.070	−0.148	0.747***
		(0.118)	(0.099)	(0.102)	(0.104)	(0.114)	(0.107)	(0.107)	(0.114)	(0.105)	(0.124)	(0.108)
	FF5 alpha	0.418***	0.258***	0.165***	0.068**	0.017	−0.046	−0.122***	−0.138***	−0.155***	−0.339***	0.757***
		(0.079)	(0.051)	(0.042)	(0.030)	(0.031)	(0.040)	(0.028)	(0.045)	(0.039)	(0.070)	(0.110)
Days 2 - 5	Return	0.035	0.047	0.021	0.042	0.045	0.020	0.013	0.012	−0.015	0.011	0.024
		(0.054)	(0.048)	(0.045)	(0.037)	(0.043)	(0.041)	(0.043)	(0.047)	(0.050)	(0.049)	(0.033)
	FF5 alpha	0.002	0.024	−0.008	0.017	0.017	−0.014	−0.015	−0.011	−0.041	0.002	0.000
		(0.029)	(0.019)	(0.012)	(0.011)	(0.011)	(0.012)	(0.013)	(0.017)	(0.027)	(0.020)	(0.037)
Days 6 - 10	Return	0.010	0.003	0.005	0.001	−0.012	−0.003	−0.032	−0.005	−0.018	−0.057	0.067**
		(0.047)	(0.043)	(0.039)	(0.042)	(0.037)	(0.038)	(0.039)	(0.041)	(0.043)	(0.046)	(0.030)
	FF5 alpha	0.037	0.017	0.023*	0.016	0.004	0.014	−0.016	0.015	−0.002	−0.031*	0.067***
		(0.023)	(0.013)	(0.013)	(0.012)	(0.010)	(0.017)	(0.011)	(0.011)	(0.018)	(0.016)	(0.025)

Table 3: **Bivariate Portfolios of Stocks Sorted by Illiquidity and *DOTS***

This table reports equal-weighted returns and Fama and French (2015) five-factor alphas of bivariate portfolios based on the Amihud (2002) illiquidity measure (*ILLIQ*) and the distance between option-implied and observed stock prices measure (*DOTS*). First, quintile portfolios are formed by sorting the optionable stocks based on *ILLIQ* in the sorting month. Then, within each *ILLIQ* quintile, stocks are sorted into quintile portfolios based on *DOTS*. We report daily average figures, for holding periods that include the first day after portfolio formation (Day 1), the second to fifth day after formation (Days 2-5), and the sixth to tenth day after formation (Days 6-10). The column labelled Low-High shows the difference between "Low ILLIQ" and "High ILLIQ", which represents going long the most liquid stocks and going short the most illiquid stocks. The row labelled Low-High shows the difference between "Low DOTS" and "High DOTS", which represents going long the lowest *DOTS* stocks and going short the highest *DOTS* stocks. The statistical significance of the average returns and alphas is represented by asterisks, where ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively. Newey and West (1987) standard errors are reported in parenthesis.

Holding Period			Low ILLIQ	High ILLIQ	Low-High
Day 1	Return	Low DOTS	0.445***	0.568***	−0.124
			(0.094)	(0.149)	(0.095)
		High DOTS	0.048	−0.297**	0.345***
			(0.106)	(0.144)	(0.078)
		Low-High	0.397***	0.865***	−0.469***
			(0.060)	(0.105)	(0.099)
	FF5 Alpha	Low DOTS	0.258***	0.413***	−0.155**
			(0.045)	(0.077)	(0.077)
		High DOTS	−0.153***	−0.429***	0.276***
			(0.036)	(0.066)	(0.066)
		Low-High	0.412***	0.842***	−0.431***
			(0.059)	(0.107)	(0.098)
Days 2-5	Return	Low DOTS	0.075	0.055	0.02
			(0.052)	(0.063)	(0.036)
		High DOTS	0.041	−0.022	0.062*
			(0.046)	(0.067)	(0.036)
		Low-High	0.035*	0.077**	−0.043
			(0.021)	(0.031)	(0.037)
	FF5 Alpha	Low DOTS	0.050***	0.044*	0.006
			(0.018)	(0.023)	(0.026)
		High DOTS	0.016	−0.038	0.055**
			(0.011)	(0.025)	(0.026)
		Low-High	0.033	0.083***	−0.049
			(0.022)	(0.031)	(0.038)
Days 6-10	Return	Low DOTS	−0.011	0.007	−0.018
			(0.042)	(0.049)	(0.037)
		High DOTS	−0.029	−0.042	0.013
			(0.046)	(0.059)	(0.042)
		Low-High	0.018	0.049*	−0.031
			(0.021)	(0.027)	(0.027)
	FF5 Alpha	Low DOTS	0.018	0.029	−0.011
			(0.012)	(0.025)	(0.026)
		High DOTS	−0.005	−0.024	0.018
			(0.013)	(0.029)	(0.030)
		Low-High	0.023	0.052**	−0.029
			(0.021)	(0.026)	(0.030)

Table 4: **Bivariate Portfolios of Stocks Sorted by Shorting Fees and *DOTS***

This table reports equal-weighted returns and Fama and French (2015) five-factor alphas of bivariate portfolios based on shorting fees on the portfolio formation date (*FEE*) and the distance between option-implied and observed stock prices measure (*DOTS*). The daily shorting fees are from the Markit database, which covers the period between July 2006 and December 2013, restricting the sample used for this test to that period. Portfolios are first formed by sorting the optionable stocks based on *FEE*. Then, within each *FEE* quintile, stocks are sorted into quintile portfolios based on *DOTS*. We report daily average figures, for holding periods that include only the first day after portfolio formation (Day 1), the second to fifth day after formation (Days 2-5), and the sixth to tenth day after formation (Days 6-10). The column labelled Low-High shows the difference between "Low FEE" and "High FEE", which represents going long the lowest fee stocks and going short the highest fee stocks. The row labelled Low-High shows the difference between "Low DOTS" and "High DOTS", which represents going long the lowest *DOTS* stocks and going short the highest *DOTS* stocks. The statistical significance of the average returns and alphas is represented by asterisks, where ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively. Newey and West (1987) standard errors are reported in parenthesis.

Holding Period			Low FEE	High FEE	Low-High
Day 1	Return	Low DOTS	0.259	0.049	0.210***
			(0.205)	(0.208)	(0.065)
		High DOTS	−0.055	−0.281	0.226***
			(0.207)	(0.220)	(0.064)
		Low-High	0.314***	0.330***	−0.016
			(0.064)	(0.084)	(0.077)
	FF5 Alpha	Low DOTS	0.240***	0.041	0.200***
			(0.044)	(0.076)	(0.067)
		High DOTS	−0.137***	−0.328***	0.192***
			(0.041)	(0.061)	(0.048)
		Low-High	0.377***	0.369***	0.008
			(0.059)	(0.090)	(0.090)
Days 2-5	Return	Low DOTS	−0.027	−0.058	0.031
			(0.091)	(0.097)	(0.036)
		High DOTS	−0.027	−0.087	0.06
			(0.084)	(0.109)	(0.051)
		Low-High	0	0.029	−0.029
			(0.023)	(0.043)	(0.058)
	FF5 Alpha	Low DOTS	−0.006	−0.022	0.017
			(0.018)	(0.028)	(0.037)
		High DOTS	0.003	−0.051	0.054
			(0.023)	(0.038)	(0.050)
		Low-High	−0.009	0.028	−0.037
			(0.024)	(0.048)	(0.064)
Days 6-10	Return	Low DOTS	0.117*	0.107	0.009
			(0.069)	(0.084)	(0.026)
		High DOTS	0.07	0.026	0.044
			(0.074)	(0.106)	(0.043)
		Low-High	0.046*	0.081*	−0.035
			(0.023)	(0.044)	(0.036)
	FF5 Alpha	Low DOTS	0.024	0.025	−0.001
			(0.016)	(0.031)	(0.025)
		High DOTS	−0.008	−0.076**	0.068*
			(0.014)	(0.033)	(0.035)
		Low-High	0.033	0.101**	−0.069*
			(0.022)	(0.044)	(0.038)

Table 5: **Univariate Analysis of Subsample of Stocks with Zero Option Volume**

This table reports excess returns (Return) and Fama and French (2015) five-factor alphas (FF5 Alpha) of portfolios formed based on the distance between option-implied and observed stock prices (*DOTS*). This test focuses on a subsample of stocks which options have zero trading volume on the sorting date (across all strikes and maturities), for which the cross-section contains 281 stocks on average. It reports daily average figures, for holding periods that include only the first day after portfolio formation (Day 1), the second to fifth day after formation (Days 2-5), and the sixth to tenth day after formation (Days 6-10). Portfolio 1 (Low DOTS) contains stocks with the lowest *DOTS*, and Portfolio 10 (High DOTS) contains stocks with the highest *DOTS* on the last trading day of the month. Panel A presents the results for equal-weighted returns across the stocks in each decile, and Panel B presents value-weighted returns, using the stocks' market capitalisations on the sorting date as weights. Column Low-High represents the results for buying the "Low DOTS" portfolio and shorting the "High DOTS" portfolio. The statistical significance of the average returns and alphas is represented by asterisks, where ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively. Newey and West (1987) standard errors are reported in parenthesis.

Panel A: Equal-Weighted Portfolios

Holding Period		Low DOTS	2	3	4	5	6	7	8	9	High DOTS	Low-High
Day 1	Return	0.559***	0.411***	0.277**	0.217**	0.157	0.121	0.089	0.067	−0.074	−0.215	0.774***
		(0.134)	(0.112)	(0.111)	(0.108)	(0.114)	(0.116)	(0.107)	(0.106)	(0.115)	(0.134)	(0.101)
	FF5 alpha	0.383***	0.229***	0.073**	0.033	−0.058	−0.073*	−0.096**	−0.131***	−0.245***	−0.379***	0.762***
		(0.070)	(0.055)	(0.032)	(0.044)	(0.045)	(0.044)	(0.038)	(0.039)	(0.051)	(0.055)	(0.105)
Days 2 - 5	Return	0.062	0.016	0.018	0.000	−0.014	0.008	−0.021	−0.024	0.003	−0.027	0.089***
		(0.056)	(0.048)	(0.049)	(0.048)	(0.044)	(0.045)	(0.041)	(0.049)	(0.056)	(0.057)	(0.031)
	FF5 alpha	0.044*	−0.004	−0.000	−0.019	−0.035*	−0.008	−0.040*	−0.042**	−0.007	−0.039	0.083**
		(0.024)	(0.020)	(0.022)	(0.018)	(0.019)	(0.014)	(0.022)	(0.020)	(0.025)	(0.026)	(0.032)
Days 6 - 10	Return	0.033	0.034	0.003	0.003	0.030	0.014	−0.008	0.021	−0.022	−0.043	0.076***
		(0.046)	(0.039)	(0.038)	(0.038)	(0.039)	(0.038)	(0.040)	(0.043)	(0.041)	(0.053)	(0.028)
	FF5 alpha	0.039	0.038**	0.005	0.008	0.027	0.011	−0.005	0.015	−0.025	−0.037	0.075***
		(0.023)	(0.018)	(0.014)	(0.015)	(0.018)	(0.015)	(0.021)	(0.014)	(0.019)	(0.028)	(0.027)

Panel B: Value-Weighted Portfolios

Holding Period		Low DOTS	2	3	4	5	6	7	8	9	High DOTS	Low-High
Day 1	Return	0.601***	0.388***	0.324***	0.243**	0.221**	0.207**	0.162*	0.132	0.019	−0.148	0.749***
		(0.120)	(0.105)	(0.103)	(0.099)	(0.105)	(0.096)	(0.093)	(0.103)	(0.106)	(0.135)	(0.103)
	FF5 alpha	0.402***	0.193***	0.089**	0.023	−0.010	0.007	−0.066*	−0.111**	−0.195***	−0.322***	0.723***
		(0.069)	(0.053)	(0.043)	(0.047)	(0.043)	(0.049)	(0.038)	(0.044)	(0.052)	(0.061)	(0.105)
Days 2 - 5	Return	0.072	0.034	0.023	−0.004	−0.035	−0.032	−0.001	−0.025	−0.020	−0.020	0.091***
		(0.049)	(0.046)	(0.045)	(0.044)	(0.040)	(0.043)	(0.038)	(0.040)	(0.042)	(0.048)	(0.024)
	FF5 alpha	0.043*	0.007	−0.001	−0.029	−0.063***	−0.056***	−0.027	−0.047**	−0.033**	−0.035	0.078***
		(0.025)	(0.022)	(0.021)	(0.020)	(0.019)	(0.020)	(0.025)	(0.020)	(0.016)	(0.022)	(0.024)
Days 6 - 10	Return	0.040	0.033	0.000	−0.006	0.025	−0.007	−0.034	0.016	0.004	−0.052	0.092***
		(0.045)	(0.038)	(0.034)	(0.034)	(0.036)	(0.038)	(0.036)	(0.040)	(0.036)	(0.047)	(0.032)
	FF5 alpha	0.041	0.034*	−0.002	−0.009	0.017	−0.013	−0.032*	0.007	−0.002	−0.053**	0.094***
		(0.026)	(0.018)	(0.017)	(0.013)	(0.012)	(0.012)	(0.017)	(0.017)	(0.017)	(0.024)	(0.034)

Table 6: **Univariate Decile Portfolios of Stocks Sorted by *DOTS* - Subsample of CBOE Penny Pilot Stocks**

This table reports excess returns (Return) and Fama and French (2015) five-factor alphas (FF5 Alpha) of portfolios formed based on the distance between option-implied and observed stock prices (*DOTS*). This test focuses on a subsample of stocks that are part of the CBOE's Penny Pilot Program on the sorting date, for which the cross-section contains 225 stocks on average. It reports daily average figures, for holding periods that include only the first day after portfolio formation (Day 1), the second to fifth day after formation (Days 2-5), and the sixth to tenth day after formation (Days 6-10). Portfolio 1 (Low DOTS) contains stocks with the lowest *DOTS*, and Portfolio 10 (High DOTS) contains stocks with the highest *DOTS* on the last trading day of the month. Panel A presents the results for equal-weighted returns across the stocks in each decile, and Panel B presents value-weighted returns, using the stocks' market capitalisations on the sorting date as weights. Column Low-High represents the results for buying the "Low DOTS" portfolio and shorting the "High DOTS" portfolio. The statistical significance of the average returns and alphas is represented by asterisks, where ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively. Newey and West (1987) standard errors are reported in parenthesis.

Panel A: Equal-Weighted Portfolios

Holding Period		Low DOTS	2	3	4	5	6	7	8	9	High DOTS	Low-High
Day 1	Return	0.395**	0.244	0.160	0.223	0.087	0.083	0.102	0.110	0.086	−0.005	0.400***
		(0.200)	(0.202)	(0.210)	(0.212)	(0.235)	(0.235)	(0.230)	(0.235)	(0.225)	(0.266)	(0.122)
	FF5 alpha	0.280***	0.098*	0.057	0.070	−0.040	−0.068	−0.069	−0.062	−0.060	−0.209**	0.489***
		(0.050)	(0.054)	(0.068)	(0.070)	(0.041)	(0.070)	(0.046)	(0.079)	(0.078)	(0.095)	(0.105)
Days 2 - 5	Return	0.033	0.015	0.058	0.042	−0.026	−0.051	−0.002	0.025	0.039	0.112	−0.079
		(0.096)	(0.117)	(0.094)	(0.087)	(0.103)	(0.085)	(0.103)	(0.095)	(0.096)	(0.135)	(0.090)
	FF5 alpha	0.066**	0.059	0.084***	0.063***	0.010	−0.016	0.043	0.057*	0.076	0.174*	−0.108
		(0.033)	(0.041)	(0.028)	(0.021)	(0.020)	(0.024)	(0.030)	(0.032)	(0.047)	(0.091)	(0.091)
Days 6 - 10	Return	0.139	0.115	0.122*	0.106	0.127*	0.118*	0.094	0.083	0.062	0.044	0.095
		(0.105)	(0.078)	(0.071)	(0.074)	(0.075)	(0.067)	(0.070)	(0.096)	(0.102)	(0.125)	(0.077)
	FF5 alpha	0.073	0.044	0.047**	0.026	0.064***	0.029	0.017	0.005	−0.013	−0.005	0.079
		(0.052)	(0.030)	(0.019)	(0.022)	(0.021)	(0.027)	(0.020)	(0.019)	(0.032)	(0.043)	(0.078)

Panel B: Value-Weighted Portfolios

Holding Period		Low DOTS	2	3	4	5	6	7	8	9	High DOTS	Low-High
Day 1	Return	0.318*	0.151	0.162	0.224	0.185	0.098	0.142	0.048	0.080	−0.053	0.371***
		(0.191)	(0.185)	(0.192)	(0.178)	(0.187)	(0.198)	(0.201)	(0.237)	(0.226)	(0.244)	(0.107)
	FF5 alpha	0.197***	0.004	0.049	0.096*	0.052	−0.027	0.006	−0.193*	−0.066	−0.282***	0.479***
		(0.062)	(0.055)	(0.057)	(0.053)	(0.044)	(0.072)	(0.036)	(0.112)	(0.072)	(0.098)	(0.117)
Days 2 - 5	Return	−0.021	−0.030	0.013	0.032	−0.030	−0.065	−0.014	−0.010	−0.021	0.045	−0.066
		(0.089)	(0.094)	(0.087)	(0.075)	(0.078)	(0.064)	(0.070)	(0.085)	(0.084)	(0.097)	(0.060)
	FF5 alpha	−0.002	0.006	0.034	0.056**	−0.005	−0.045*	0.008	0.016	0.017	0.087**	−0.089
		(0.039)	(0.027)	(0.028)	(0.022)	(0.017)	(0.026)	(0.019)	(0.034)	(0.033)	(0.043)	(0.065)
Days 6 - 10	Return	0.100	0.071	0.082	0.073	0.087*	0.056	0.081	0.033	0.058	−0.012	0.112
		(0.081)	(0.059)	(0.057)	(0.058)	(0.048)	(0.052)	(0.057)	(0.087)	(0.084)	(0.113)	(0.083)
	FF5 alpha	0.048	−0.005	0.019	−0.002	0.027	−0.024	0.008	−0.038	−0.010	−0.067*	0.115
		(0.044)	(0.016)	(0.024)	(0.016)	(0.028)	(0.021)	(0.018)	(0.032)	(0.024)	(0.036)	(0.072)

Table 7: **Decomposition of DOTS Predictability into Price Pressure and Informed Trading**

This table decomposes the predictive ability of DOTS into the component that is attributable to price pressure in the stock market (Panel A), and the component attributable to informed trading in the options market (Panel B). Portfolios are formed based on independent sorts of the *DOTS* measure and stock order imbalances measured as the ratio of the dollar value of buyer-initiated trades to the dollar value of seller-initiated trades (*OIB*). On the last trading day of each month, stocks are sorted into quintiles of DOTS. "Low DOTS"("High DOTS") refers to the stocks DOTS quintile 1(5). On the same date, stocks are classified as "Above Med OIB"("Below Med OIB") if the order imbalance is above(below) than the cross-sectional median. In Panel A, the portfolio is long stocks having "Low DOTS" and "Below Med OIB", and short stocks having "High DOTS" and "Above Med OIB". In Panel B, the portfolio is long stocks having "Low DOTS" and "Above Med OIB", and short stocks having "High DOTS" and "Below Med OIB". We report average observed stock returns and average option-implied stock returns for the formation date (Day 0), and daily average portfolio returns and Fama and French (2015) five-factor alphas ("FF5 alpha") for holding periods that include only the first day after portfolio formation (Day 1), the second to fifth day after formation (Days 2-5), and the sixth to tenth day after formation (Days 6-10). The sample covers NYSE stocks during the period 1996-2010. The last row of each panel reports the average number of stocks in each leg and in the long-short portfolio. The statistical significance of the average returns and alphas is represented by asterisks, where ***, **, and * represent significance at the 1%, 5%, and 10% level, respectively. Newey and West (1987) standard errors are reported in parenthesis.

Panel A: DOTS as a Measure of Price Pressure in the Stock Market

Time Period		Long (Low DOTS + Below Med OIB)	Short (High DOTS + Above Med OIB)	Long - Short
Day 0 (Sort Date)	Observed Return	−0.742***	1.040***	−1.783***
		(0.109)	(0.137)	(0.138)
	Option-Implied Return	−0.413***	0.640***	−1.053***
		(0.094)	(0.114)	(0.098)
Day 1	Return	0.663***	−0.042	0.705***
		(0.115)	(0.137)	(0.085)
	FF5 alpha	0.349***	−0.343***	0.692***
		(0.056)	(0.056)	(0.085)
Days 2 - 5	Return	0.045	−0.022	0.067**
		(0.055)	(0.055)	(0.026)
	FF5 alpha	0.031*	−0.032	0.063**
		(0.018)	(0.022)	(0.027)
Days 6 - 10	Return	−0.008	−0.038	0.030*
		(0.047)	(0.050)	(0.018)
	FF5 alpha	0.006	−0.023*	0.029*
		(0.015)	(0.013)	(0.015)
	# Stocks	82.3	78.0	160.3

Panel B: DOTS as a Measure of Informed Trading in the Options Market

Time Period		Long (Low DOTS + Above Med OIB)	Short (High DOTS + Below Med OIB)	Long - Short
Day 0 (Sort Date)	Observed Return	0.385***	−0.04	0.425***
		(0.122)	(0.114)	(0.116)
	Option-Implied Return	0.597***	−0.335***	0.932***
		(0.111)	(0.108)	(0.122)
Day 1	Return	0.419***	0.174	0.245***
		(0.109)	(0.117)	(0.057)
	FF5 alpha	0.139***	−0.136***	0.275***
		(0.038)	(0.049)	(0.056)
Days 2 - 5	Return	0.023	−0.012	0.035*
		(0.059)	(0.061)	(0.018)
	FF5 alpha	0.011	−0.019	0.030
		(0.022)	(0.020)	(0.020)
Days 6 - 10	Return	−0.016	−0.029	0.014
		(0.052)	(0.048)	(0.020)
	FF5 alpha	0.002	−0.015	0.017
		(0.018)	(0.017)	(0.018)
	# Stocks	45.9	50.4	96.3

Table 8: **Univariate Decile Portfolios of Stocks Sorted by *DOTS* - Monthly Holding Period**

This table reports monthly returns allowing for zero, one, and five rest days between the formation date and the holding period. It reports excess returns (Return) and Fama and French (2015) five-factor alphas (FF5 Alpha) of portfolios formed based on the distance between option-implied and observed stock prices (*DOTS*). Portfolio 1 (Low DOTS) contains stocks with the lowest *DOTS*, and Portfolio 10 (High DOTS) contains stocks with the highest *DOTS* on the last trading day of the month. Panel A presents the results for equal-weighted returns and Panel B presents value-weighted returns, using the stocks' market capitalisations on the sorting date as weights. Column Low-High represents the results for buying the "Low DOTS" portfolio and shorting the "High DOTS" portfolio. The statistical significance of the average returns and alphas is represented by asterisks, where ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively. Newey and West (1987) standard errors are reported in parenthesis.

Panel A: Equal-Weighted Portfolios

Rest Period		Low DOTS	2	3	4	5	6	7	8	9	High DOTS	Low-High
0 days	Return	1.353***	0.949**	0.835*	0.799*	0.938**	0.887**	0.525	0.570	0.439	−0.164	1.518***
		(0.458)	(0.416)	(0.428)	(0.413)	(0.406)	(0.408)	(0.418)	(0.444)	(0.467)	(0.511)	(0.189)
	FF5 alpha	0.477**	0.130	0.112	0.163*	0.250**	0.196*	−0.161	−0.208	−0.361**	−1.001***	1.478***
		(0.200)	(0.131)	(0.105)	(0.083)	(0.106)	(0.113)	(0.106)	(0.129)	(0.141)	(0.180)	(0.193)
1 day	Return	0.796*	0.622	0.592	0.570	0.777**	0.738**	0.463	0.543	0.509	0.091	0.704***
		(0.415)	(0.380)	(0.387)	(0.363)	(0.354)	(0.370)	(0.366)	(0.393)	(0.412)	(0.458)	(0.150)
	FF5 alpha	0.118	−0.035	0.069	0.108	0.297**	0.225**	−0.048	−0.005	−0.098	−0.564***	0.682***
		(0.198)	(0.135)	(0.104)	(0.079)	(0.118)	(0.112)	(0.114)	(0.120)	(0.136)	(0.181)	(0.155)
5 days	Return	0.592*	0.504*	0.453	0.372	0.613**	0.554**	0.469*	0.484	0.473	0.202	0.390***
		(0.332)	(0.283)	(0.281)	(0.273)	(0.243)	(0.261)	(0.266)	(0.305)	(0.305)	(0.348)	(0.124)
	FF5 alpha	−0.007	−0.072	−0.008	−0.043	0.210**	0.156	0.008	0.017	−0.096	−0.399**	0.391***
		(0.203)	(0.146)	(0.098)	(0.078)	(0.097)	(0.098)	(0.109)	(0.109)	(0.128)	(0.182)	(0.124)

Panel B: Value-Weighted Portfolios

Rest Period		Low DOTS	2	3	4	5	6	7	8	9	High DOTS	Low-High
0 days	Return	1.119**	0.807**	0.755**	0.824**	0.639	0.718*	0.278	0.343	0.317	0.019	1.100***
		(0.437)	(0.360)	(0.369)	(0.358)	(0.398)	(0.394)	(0.366)	(0.429)	(0.422)	(0.450)	(0.272)
	FF5 alpha	0.391*	0.041	0.239*	0.346***	0.143	0.130	−0.215*	−0.290*	−0.383**	−0.495**	0.886***
		(0.222)	(0.188)	(0.126)	(0.125)	(0.111)	(0.185)	(0.123)	(0.149)	(0.174)	(0.201)	(0.301)
1 day	Return	0.535	0.348	0.394	0.538*	0.384	0.544	0.169	0.255	0.264	0.189	0.346
		(0.397)	(0.324)	(0.346)	(0.317)	(0.344)	(0.361)	(0.310)	(0.366)	(0.370)	(0.388)	(0.251)
	FF5 alpha	0.123	−0.162	0.097	0.253**	0.119	0.164	−0.147	−0.133	−0.196	−0.096	0.219
		(0.211)	(0.176)	(0.112)	(0.112)	(0.098)	(0.163)	(0.110)	(0.127)	(0.148)	(0.175)	(0.261)
5 days	Return	0.411	0.178	0.315	0.399	0.207	0.469*	0.119	0.222	0.362	0.153	0.257
		(0.299)	(0.251)	(0.253)	(0.253)	(0.265)	(0.257)	(0.224)	(0.269)	(0.264)	(0.285)	(0.197)
	FF5 alpha	0.095	−0.254	0.134	0.173	0.044	0.212	−0.145	−0.053	−0.014	−0.131	0.227
		(0.185)	(0.175)	(0.098)	(0.123)	(0.091)	(0.140)	(0.096)	(0.119)	(0.121)	(0.144)	(0.184)

Table 9: **Cross-Sectional Regressions**

This table reports the results of stock-level Fama-MacBeth regressions, where the dependent variable is the one-day return of a stock for the first day after portfolio formation. The formation date is the last trading day of the month and the holding day is the first trading day of the month after formation. The controls include the dummy variables *DOTS1* and *DOTS10* for whether a stock belongs to either the bottom or the top *DOTS* decile, respectively. The remaining control variables are described in Section 4.6. The statistical significance of the regression coefficients is represented by asterisks, where ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively. The last row reports the average adjusted R-squared values. Newey and West (1987) standard errors are reported in parenthesis.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DOTS1	0.431***	0.429***	0.468***	0.444***	0.509***	0.448***	0.518***	0.459***
	(0.065)	(0.062)	(0.063)	(0.061)	(0.069)	(0.064)	(0.066)	(0.062)
DOTS10	−0.382***	−0.350***	−0.351***	−0.336***	−0.373***	−0.350***	−0.349***	−0.322***
	(0.056)	(0.044)	(0.048)	(0.043)	(0.071)	(0.060)	(0.060)	(0.056)
REV		−0.010***		−0.012***		−0.011**		−0.012***
		(0.004)		(0.003)		(0.005)		(0.005)
VOLAT		−0.025		−0.021		0.017		−0.005
		(0.021)		(0.015)		(0.028)		(0.022)
CP VOLUME		0.014**		0.017***		0.020**		0.020**
		(0.007)		(0.006)		(0.009)		(0.008)
O/S RATIO		−0.286**		−0.302**		−0.141		−0.073
		(0.130)		(0.119)		(0.179)		(0.192)
OIB						−0.146***		−0.129***
						(0.032)		(0.027)
BETA			0.019	0.041			0.034	0.054
			(0.036)	(0.031)			(0.051)	(0.042)
SIZE			0.044***	0.041***			0.021	0.016
			(0.014)	(0.012)			(0.015)	(0.014)
MB			−0.017*	−0.013			−0.017	−0.017
			(0.010)	(0.009)			(0.012)	(0.011)
MOM			−0.001	−0.001			−0.001	−0.001
			(0.001)	(0.001)			(0.001)	(0.001)
ILLIQ			−1.045	−0.04			−7.358	−7.648
			(2.335)	(2.514)			(5.434)	(5.567)
INTERCEPT	0.162	0.278***	−0.204	−0.12	0.269**	0.458***	0.044	0.280*
	(0.111)	(0.075)	(0.153)	(0.127)	(0.114)	(0.073)	(0.155)	(0.146)
ADJRSQ	0.008***	0.048***	0.068***	0.086***	0.010***	0.065***	0.079***	0.109***
	(0.001)	(0.005)	(0.006)	(0.007)	(0.001)	(0.006)	(0.007)	(0.008)
Obs (Time-Series)	216	216	216	216	180	180	180	180
Obs (Panel)	218,071	218,071	218,071	218,071	100,569	100,569	100,569	100,569

Table 10: **Time-Variation in *DOTS* Strategy Returns**

This table shows the results of time-series regressions of one-day *DOTS* strategy returns on lagged proxies for funding liquidity and market states. The predictive variables include the average TED spread in the five trading days leading to (and including) the sorting date, the average VIX Index in the five trading days leading to (and including) the sorting date. In Panel A, the dependent variable is the one-day return from going long the lowest *DOTS* stocks and simultaneously going short the highest *DOTS* stocks. Panel B reports the results for the long leg of the *DOTS* strategy, while Panel C reports the results of the short leg only. The statistical significance of the regression coefficients is represented by asterisks, where ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively. Newey and West (1987) standard errors are reported in parenthesis.

Panel A: Long-Short Portfolio Based on DOTS

	(1)	(2)	(3)	(4)
INTERCEPT	0.820***	0.600***	0.097	0.094
	(0.122)	(0.161)	(0.183)	(0.192)
TED		0.437**		0.216
		(0.218)		(0.249)
VIX			0.534***	0.457**
			(0.162)	(0.211)
MKTRF	−0.044	−0.029	−0.011	−0.008
	(0.049)	(0.043)	(0.039)	(0.039)
SMB	0.129	0.143	0.186	0.184*
	(0.116)	(0.109)	(0.113)	(0.109)
HML	−0.212*	−0.223**	−0.138	−0.155*
	(0.110)	(0.100)	(0.092)	(0.087)
ADJRSQ	0.042	0.077	0.129	0.13

Continued on next page

Table 10: **Continued**

Panel B: Long Leg of DOTS Strategy

	(1)	(2)	(3)	(4)
INTERCEPT	0.464***	0.255**	0.087	0.081
	(0.087)	(0.098)	(0.145)	(0.132)
TED		0.416***		0.340**
		(0.108)		(0.143)
VIX			0.279**	0.157
			(0.118)	(0.140)
MKTRF	1.067***	1.082***	1.084***	1.089***
	(0.032)	(0.030)	(0.028)	(0.028)
SMB	0.944***	0.957***	0.974***	0.972***
	(0.098)	(0.093)	(0.103)	(0.100)
HML	−0.229**	−0.240***	−0.191**	−0.217***
	(0.096)	(0.084)	(0.091)	(0.080)
ADJRSQ	0.895	0.901	0.898	0.901

Panel C: Short Leg of DOTS Strategy

	(1)	(2)	(3)	(4)
INTERCEPT	−0.356***	−0.345***	−0.01	−0.012
	(0.059)	(0.093)	(0.152)	(0.140)
TED		−0.022		0.124
		(0.140)		(0.151)
VIX			−0.255*	−0.300**
			(0.134)	(0.137)
MKTRF	1.111***	1.111***	1.096***	1.097***
	(0.038)	(0.040)	(0.035)	(0.037)
SMB	0.815***	0.815***	0.788***	0.788***
	(0.081)	(0.082)	(0.075)	(0.076)
HML	−0.017	−0.017	−0.053	−0.062
	(0.100)	(0.101)	(0.110)	(0.110)
ADJRSQ	0.930	0.930	0.933	0.933